Spotting Online News: A Mixed Method Study of Online News Engagement and Perceptions on Misinformation Interventions

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Misinformation permeates online news media, making it hard for users to trust and verify content. Building upon prior work that highlights online news challenges and the importance of digital literacy skills, we examine user digital media skills, online news consumption behaviors, and perceptions of current misinformation tools. To better understand these dynamics, we conducted a formative, mixed methods study (n=34) that included a survey, two weeks of browser-based application logging using a Chrome plugin, and follow-up semi-structured interviews. Contradictions in the survey and log results indicate that participants in our sample often overestimate their news consumption habits. While information and news media literacy scores are generally high, less than half (47%, 16/34) exhibit lateral reading. We provide insights into users' challenges in navigating today's information landscape and propose effective integrated solutions. Interview findings inform the design of online news interventions and personal informatics tools to further improve media literacy while maintaining user privacy.

CCS Concepts: • **Human-centered computing** → **Human computer interaction (HCI)**; **Empirical studies in HCI**; *HCI design and evaluation methods*; *User studies*; Web-based interaction;

Additional Key Words and Phrases: Online news, Media literacy, Browsing habits, Interventions, Media bias

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1 Introduction

The rise of online news media websites has increased access to information. However, with this increased access has come concerns regarding individuals' ability to discern accurate news from false and misleading content [50, 77, 120]. In a 2016 survey by Pew Research Center, approximately a third (32%) of U.S. adults say they often encounter made-up political news online, and about half

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(51%) report frequently seeing somewhat inaccurate news [14]. Among those who report these issues (82%), the majority believe it causes serious confusion about the basic facts of current issues and events [14]. Moreover, repeated exposure to news from untrustworthy (*e.g.,* Breitbart, Infowars), partisan (*e.g.,* Fox News), satirical sources (*e.g.,* The Onion, ClickHole) and fake news sites (*e.g.,* ABCNews.com.co) heightens the risk of encountering misinformation [62, 74, 88, 112]. This has harmful implications for society and politics, leading to polarization [37], legislative gridlock [54], and reports of violence (e.g. [104]).

To combat this issue, prior work has focused on studying behaviors of social media users in a broader sense of dealing with fake news spreading [33, 101], misinformation sharing and truth discernment [25, 43, 86, 87]. Other initiatives include understanding online news behaviors [15], development of web-browser plugins for timely fake news detection [82] and classification purpose [40]. However, there remain gaps in our understanding of these challenges. Specifically, how people consume news from news websites and how this differs from fake news sites [51]. We lack insights into the behaviors, patterns, and motivations that influence news consumption on credible versus misinformation-spreading platforms. Moreover, a recent systematic review suggests most of the current research, about 61% is focused only on proposing ways to detect online misinformation [9]. Only a small portion, just 2% is dedicated to developing and evaluating digital intervention techniques [9]. Recognizing this imbalance in current research efforts, our aim is to take a fresh look at everyday user behaviors and their online interactions. This will help us understand their perceptions of the current online news media landscape and lay the groundwork for designing effective human-centered interventions against online misinformation. As a result, our study aims to answer the following research questions: ***(RQ1)*** *How do users' perceptions of their news consumption (e.g., time spent, news sources) and habits (e.g., engaging in lateral reading) align with their observed behavior?* ***(RQ2)*** *How do user features such as literacy level relate to discernment abilities in news credibility evaluations, and to what extent does this association impact their online information consumption behavior?* ***(RQ3)*** *And, what challenges and benefits do users perceive about current and future online misinformation intervention tools?*

To address our research questions, we used an exploratory mixed methods approach to conduct a user study with 34 participants. Our survey gathered quantitative data on demographics, news habits, online literacy, and several other metrics while the plugin tracked daily browsing sessions. Follow-up interviews offer qualitative insights into perceptions of current intervention effectiveness and future intervention acceptance. Participants' weblogs and survey data indicate active browsing behavior within the study period. However, there is a notable difference between what people say about their news consumption and their observed behavior. Those who engage in more news sessions during browsing tend to read a higher volume of news articles and encounter a greater number of news pieces. Additionally, those who engage in more lateral reading sessions demonstrate higher levels of media literacy, with increased lateral reading and fact-checking behaviors correlating with a decreased likelihood of sharing articles ($p < 0.05$).

Building upon these findings, we proposed the integration of personal news informatics with conventional misinformation interventions to provide users with a more accurate understanding of their consumption behavior. Our research offers implications for news intervention tool developers and, most importantly, end-users, increasing trust, user engagement and ease of navigation in the online information landscape. Our work contributes by (i) introducing a lightweight Chrome plugin tool for privately tracking news consumption, (ii) presenting results from our empirical, mixed methods study that offer a behavioral perspective on countering fake news in online news media beyond technical solutions, and (iii) offering insights into how specific user features and attributes influence critical news assessment and inform most optimal future interventions for users.

2 Related Work

In this section, we contextualize our study within the current state-of-the-art by reviewing work on online news consumption and approaches to mitigating misinformation. We also synthesize key theoretical perspectives and empirical findings that shape our understanding of how individuals engage with online news. These works were found through searches across common academic search engines and databases (e.g., Google Scholar, IEEE Xplore, ACM Digital Library) using specific search terms related to our research questions. For example, our searches focused on keywords such as "*online news engagement*", "*browsing behavior*", "*media literacy interventions*" and "*misinformation detection*". We reviewed the works that were returned, their references, and those that cited them. Where applicable, we also highlight recent work from the CHI and CSCW conference proceedings.

2.1 Background

In today's digital world, news spreads online almost instantly [31]. Numerous online platforms also allow anyone to publish content without thorough fact-checking [35]. This situation leads to an interesting mix of major publishers and citizen reporters that make up the online news production ecosystem. While this can be viewed positively, it can also make it challenging to stay well-informed [99, 110]. As noted in the introduction, one major challenge is the rise of misinformation—spreading inaccurate or deceptive content that misleads audiences, exploits cognitive framing, and distorts perceptions of reality [7, 63, 109].

Defining online misinformation is challenging, especially as the concept of "fake news" (*a subtype of misinformation*) evolves [39]. It can impact health, decision-making, and emotions as well as promote online crime [22, 23]. On the health side, for example, one in ten Americans report experiencing mental stress from false online information when surveyed [67]. This issue persisted through major events like the 2016 U.S. elections and the 2017 German elections and worsened during the COVID-19 pandemic [7, 41, 48, 89, 109]. Misinformation was even cited for causing market disruptions leading to a $130 billion (USD) loss around these times [94]. Online platforms further contribute by promoting tailored content, confirmation bias (*the tendency to search for and favor information that supports our preexisting beliefs*), and echo chambers (*an environment where a person only encounters information or opinions that reflect and reinforce their own*) [32, 44, 78].

One key factor in the rapid spread of online misinformation is the lack of digital media literacy skills [45]. Individuals with low digital literacy are more susceptible to false information [102]. A study shows only 17% of US adults feel confident in learning new information online [53], emphasizing the need for better preparation to navigate the digital landscape [7]. Media literacy skills, improved by techniques like lateral reading [116], are vital for evaluating source credibility, developing critical thinking and building resilience against misinformation [30, 45, 68, 72, 75, 121]. Thus, developing these skills is crucial for effectively navigating today's complex information landscape. In the later sections, we will look into understanding news consumption, tracking data related to online behaviors, and existing approaches against misinformation.

2.2 Understanding News Consumption Trends and Misinformation

Misinformation in the news can influence people's behaviors and increase social media sharing [114]. This highlights the critical need to study news consumption patterns to understand engagement with misinformation [117]. Many people tend to overestimate the amount of news they consume, especially political news. This overestimation can lead them to believe they are well-informed, even when their exposure to reliable information is actually limited [59, 93]. This makes them more vulnerable to misinformation as they may not critically assess the accuracy or reliability of the information they encounter. Studies on news consumption behavior also indicate that excessive news consumption has been linked to negative mental health effects and news avoidance [11, 79].

Despite promising research efforts, fully understanding news consumption remains challenging because the dynamic nature of news consumption behavior necessitates a nuanced understanding of how individuals interact with news sources [97], discern credibility [85], engage in lateral reading habits [116], and share information online [80]. These complexities arise from factors such as rapidly changing digital media landscapes, heterogeneity in literacy among users, algorithmic biases shaping content visibility, and the dynamic nature of online social interactions [90]. Moreover, Xiao's study suggests that news consumption in the digital age demands thorough examination due to its connection with factors such as personality traits, media literacy, incidental exposure to news content, and misinformation engagement [117, 118]. Xiao & Su further highlight how personal factors like narcissism and news media literacy influence misinformation engagement, affecting news consumption and sharing behaviors [118]. Therefore, understanding online news engagement needs a multidimensional approach considering technological, behavioral, and societal factors. To effectively tackle misinformation, a fresh look at people's browsing habits and views on misinformation is essential. We conducted this study using a mixed methods approach to try and holistically understand these issues from users' perspectives to inform the design of effective tools and interventions. These methods have proven to be particularly well-suited for investigating this area due to the multifaceted nature of the design challenges [27, 119].

2.3 Methods and Insights from Web Monitoring Tools

Researchers use web monitoring tools to track online news consumption, providing a detailed view of user behavior [13, 15, 70]. Technological logs from these tools enable reflection on habits through data. Studies comparing self-reported internet and media usage with actual logged data generally show modest correlations [81, 98]. And, if there is a discrepancy between perceived news habits and actual data, users might experience negative reflections [12].

Building on this understanding, Flaxman *et al.* conducted a large-scale study of online news consumption, analyzing web-browsing histories of 50,000 regular news readers in the US. They found that online news consumption mirrors offline habits, with users favoring mainstream outlets [32]. Moller *et al.* used a dataset that combined online tracking data with survey data to examine factors predicting news engagement methods from the analysis of actual behavioral patterns alongside self-reported measures [70]. They found that general search-driven news use was associated with a broader information-seeking behavior and was less influenced by regular news consumption habits. Similarly, Bentley *et al.* analyzed data from 174 Americans, revealing key news consumption trends [15]. While such studies investigate news consumption patterns to understand factors influencing news engagement, they lacked thorough examnination of how users' online interactions influence their reactions to misinformation and its implications for assessment of source credibility.

Our study builds on these prior works by studying the alignment or divergence between users' perceived habits and their actual behaviors, exploring how their literacy levels influence their discernment abilities. Typically, interview-based studies lack access to online actions, and digital trace data research often lacks the context provided by in-depth interviews. Our interest lies in real-time monitoring of a participant group's web behavior to offer a more holistic understanding of how browsing features and habits (e.g., lateral reading) align with users' observed behavior.

2.4 Existing Approaches and Interventions Against Misinformation

There are numerous approaches to mitigating misinformation online. Fact-checking efforts like Factcheck.org [1], Politifact [4], Snopes [5], and rating systems like NewsGuard [3] help identify trustworthy sites and information sources as people consume news articles online. However, current methods are slow, not scalable, and often miss viral misinformation [90]. Fact-checks also struggle to reach audiences, fade over time, and may lead users to share more low-quality content [46, 73, 106]. Moreover, warnings and fact-checks often target only blatant falsehoods creating an "implied truth" effect where users assume unflagged headlines are verified [83]. This approach contrasts sharply with the pervasive nature of misinformation.

On the other hand, machine learning algorithms are widely used in fake news detection using linguistic analysis and network graph based methods to identify misleading information [20, 71, 92]. However, these often overlook user preferences and rely heavily on text content. The explainability of detection models is often low and potentially unsuitable as an intervention due to lack of transparency and poor accuracy [49, 51]. Findings about users' interventions in algorithmic news selection are also inconclusive [105]. There is also a gap in leveraging sociological and psychological perspectives through technology.

Strategies like nudges [17, 100], inoculation techniques [95], user affordances (such as accuracy assessment, trust and filter) [56], AI-based credibility indicators [66] and news credibility labels [10] have also been explored. Meanwhile, content removal or account suspension risks user dissatisfaction and disrupts news flow [107]. CSCW works like FeedReflect [18] and POP [76] offer nudging features, but their claims of improving news media literacy require validation. Techniques like aggregated news views [6] and cross-ideological feed viewing [2] lack global news integration within the main article reading interface. Unlike social media-focused efforts (e.g.,[58]), approaches must mix technology with an understanding of how people consume news from online publishers.

Therefore, effective solutions require blending technology with behavioral insights and improving media skills such as lateral reading and fact-checking. Our study seeks to understand user perceptions and preferences around existing systems and interventions to better understand design opportunities for tools that support empowered and informed citizens in the digital age.

3 Method

We conducted a two-week, mixed methods study with 34 users, which included a pre-survey on media literacy and demographics, two weeks of logging browsing sessions, and follow-up semi-structured interviews. Our approach is informed by prior research which shows that a mixed methods approach is highly effective for studying misinformation and fake news as it allows us to uncover detailed mechanisms behind misinformation behaviors and broader trends [16, 28, 29, 122], providing a holistic understanding that informs effective interventions and policies. In our study, it collectively help to understand general trends in participant habits, motivations and browsing patterns.

Application logging tracked browsing behaviors and complements our data collection by providing granular data on how participants interact with online news content. Interviews offer qualitative depth, allowing us to explore the nuanced perspectives behind the quantitative trends identified in other data sources. By comparing actual logged behaviors with reported behaviors from the surveys and interviews, we aimed to identify discrepancies and potential reasons behind them.

In the sections that follow, we describe our study participants, recruitment process, and eligibility criteria. Following this, we outline the information collected through our survey. We then describe the procedure for collecting browsing data using our chrome plugin. Finally, we describe our approach to the semi-structured interviews and data analysis.

3.1 Eligibility and Recruitment

Participants were recruited via email listservs, i.e., electronic mailing lists, word-of-mouth, and online recruitment platforms. Eligible participants were required to be 18 years or older, a U.S. citizen or a permanent resident, proficient in writing and speaking in English, and a Chrome internet browser user who regularly read online news articles using a desktop computer. We enrolled participants on a rolling schedule between *July 30, 2022* and *September 6, 2022*. A link to our online consent form was embedded in our recruitment ad, which started the study protocol. Participants were first asked to review the consent form and indicate their willingness to be contacted about participation in a follow-up debrief interview. Once completed, participants were automatically sent an email containing study protocol instructions. These instructions guided the participant through installing our plugin, registering and creating an account, and completing the online demographic questionnaire.

After approximately two weeks of application logging with the plugin, participants who consented were contacted about follow-up interviews. Once the study concluded, participants were sent a $30 digital Amazon Gift Card and plugin uninstall instructions (Figure 1). This study protocol was approved by University of Delaware Institutional Review Board (IRB Protocol #1871618-6).

3.2 Pre-Survey on Media Literacy & Demographics

A web based pre-survey was administered through Qualtrics. Participation in the survey was prompted through a button that appeared in the user interface of the Chrome extension's main display panel. The survey included open and closed-response questions and was divided into four major sections: i) A headline evaluation task (similar to [84]) where participants are asked to identify true and false headlines and indicate their likelihood of sharing them with others, ii) A section on internet usage asking how often respondents use the internet to search for news [96] on a 10-point scale, iii) A news media literacy evaluation section (measured using a multidimensional scale [115]) where participants were presented with 15 statements and asked to rate their agreement on a scale of 1 to 7, and iv) A information literacy evaluation section with four multiple-choice questions all of which have only one correct answer and three incorrect responses [19]. Finally, the survey included basic demographic information such as age, gender, ethnicity, education, and employment status. The complete questionnaire is available in our Supplementary Materials Note 6.

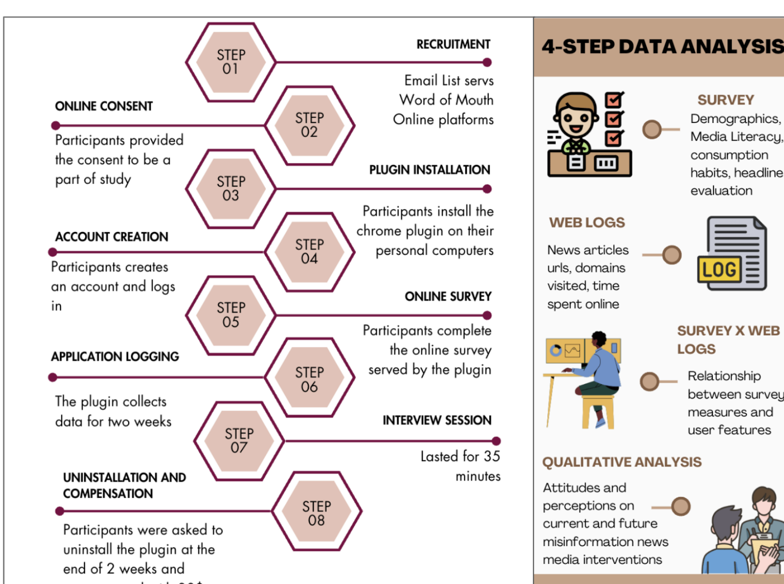


Fig. 1. Methodology for the study: Data Collection and Analysis

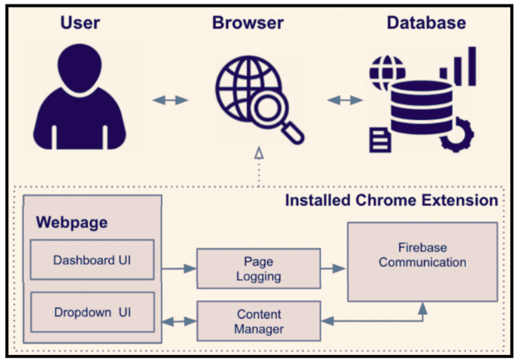


Fig. 2. Architecture Diagram of Chrome Plugin

3.2.1 Survey Analysis. We anonymized the survey-generated data by removing identifiable information post-submission. Each individual was allocated a unique, anonymous study identifier. Throughout this paper, we refer to participants (P) using an identification number (e.g., P11). Additionally, the survey linked each participant's response to their Firebase authentication user ID, allowing for merging their Qualtrics survey responses and browsing data. Of the 48 participants, 34 (70%) completed the study. The survey responses were coded and survey scale results were calculated using SPSS and STATA. We used JMP and Excel for generating descriptive statistics, exploratory visualizations, and conducting statistical tests. On average, the survey took 20 mins (SD=11.32) to complete.

3.3 Browsing Data

Using a client-server architecture similar to that of Bentley *et al.* and VanTol *et al.* [15, 111], we tracked participants' online browsing data using a Chrome plugin designed for desktop Chrome browser. Our plugin uses a Firebase database, the user's browser and a dropdown UI widget. The backend is powered by Firebase, and the front end includes HTML, Bootstrap, jQuery, D3.js, etc. The plugin does not observe online activity on other web browsers or platforms. A visual representation of this plugin is provided in Figure 2. In this study, we used email and text password methods for logins instead of Google accounts. The plugin was installed on participants' personal computers only, and is not compatible with mobile browsers or multiple Chrome instances using the same Google account. This choice of this login provided flexibility without platform restrictions, addressing privacy and security concerns by avoiding the need to link Google accounts for research purposes.

In passive mode, interactions with our plugin are limited: i) a user installs our web extension from the Chrome store using an unlisted URL, ii) creates an account, iii) logs in, iv) and v) then completes the demographic survey (powered by Qualtrics) linked on the splash screen. After completing these steps, the extension records various metadata, including domain-level information (stored in Firebase) and article URLs, article bias, timestamp, and time spent on pages. However, the plugin only records the URL when users visit web pages other than news articles. For instance, it would log that a user was visiting facebook.com but not their activity on that domain. The plugin, hence, recorded the article's full web address when the user visited a news article for a predetermined set of 513 known publisher domains (based on the AllSides dataset [8]).

To capture participants' real-time engagement with news content during active browsing sessions, the plugin uses a mechanism related to tab-switching events, and by tracking the "focus", it can determine when a user actively change from one tab to another. It is important to note limitations in webpage-to-webpage tracking. The tracking code in place records user activity, excluding inactive periods. Therefore, the reported duration reflects time spent on active browsing, including actions like clicking, scrolling, interacting with multimedia, submitting forms, and switching between tabs.

3.3.1 Browsing Data Analysis. We downloaded the browsing data from Firebase in JSON format and then cleaned and featurized the data using Python before exporting them as a CSV file. The cleaned data were analyzed using Microsoft Excel and JMP. Browsing features such as *"days active"*, *"total seconds"* and article features such as *"days with articles"*, *"total articles"*, and *"reading bias"* (*i.e., the average bias of the news they consumed*) were aggregated at the user level to provide insights into the participant's overall browsing behavior. One participant in the study stood out by reading significantly more articles (158) than others, potentially linked to their news site being set as the browser homepage. This outlier was removed during analysis. In line with our inclusion criteria, participants who fell outside of the two-week study period were excluded from the analysis of relationship trends. Once exported, these two sets of features were joined with our pre-survey data for further analysis. Full feature list and definitions are included in Supplemental Materials Note 2.

3.4 Follow-up Interview

We conducted semi-structured interviews with 15 participants who voluntarily agreed during the consent process. Among those who volunteered, participants were selected using a convenient sampling method based on a first-come, first-served approach. Initially, 25 participants volunteered for the debrief; however, we conducted interviews until reaching saturation [47, 52]. When we reached this stage, we stopped interviewing and began analyzing our collected information. This process led us to complete the follow-up interview portion of our study after interviewing 15 participants.

Among those who volunteered, participants predominantly identified as liberal or moderate politically, with a minority identifying as slightly conservative or conservative. The average age of the interview participants was approximately 32.03 years (SD= 12.12). The group included a mix of genders and racial backgrounds, with a notable representation of females (10/15), White individuals (8/15), and Black/African Americans (4/15). Educationally, most participants had completed at least a Bachelor's degree (7/15), and some had advanced to Master's (2/15) or Doctoral levels (2/15). Employment-wise, many were students (6/15) or held full-time (4/15) or part-time jobs (2/15), while others were actively seeking employment (3/15). Geographically, participants came from various states across the United States, including Delaware, Maryland, California, Connecticut, Georgia, and Rhode Island. Please refer to the Table 1 detailing the demographics of interview participants.

The primary goal of the interviews was to explore diverse perceptions of individuals regarding current tools and future misinformation interventions. To start, we asked about the general questions and background on news and misinformation, their browsing habits and how familiar they are with technology or with current tools to understand their opinions better. Interviews lasted an average of 35 mins (SD=11.814) and were audio recorded and transcribed for analysis. See the complete moderator guide in our Supplementary Materials Note 1.

3.4.1 Interview Analysis. We transcribed our interview data using Otter.AI software. Two researchers analyzed the transcribed data using an iterative thematic analysis approach by Braun and Clarke [21] which included a mixture of inductive and deductive codes on the complete responses to each interview question. We created a codebook derived from our research team's knowledge of prior work and our study protocol while allowing other codes to emerge from the data. A total of 16 codes emerged, which were divided into four high-level themes: (1) browsing session habits and encounters; (2) data privacy and security; (3) intervention acceptability; and (4) challenges, concerns, and approaches related to misinformation. To validate the codebook, a single transcript was

PID	Political Leaning	Age	Gender	Racial Identity	Education	Employment Status	State
P48	Moderate	26	Male	Asian	Master's	Student	DE
P46	Liberal	59	Female	White	Doctoral	Employed FT	MD
P24	Moderate	22	Female	White	Bachelor's	Seeking Employment	DE
P17	Moderate	21	Female	White	Bachelor's	Student	DE
P34	Extremely Liberal	20	Female	White	High School	Student	MD
P41	Liberal	27	Female	Black/African American	Bachelor's	Student	CT
P42	Slightly Conservative	30	Male	Hispanic or Latino	Associate's	Employed FT	CA
P10	Slightly Liberal	45	Female	White	Doctoral	Employed PT	DE
P30	Liberal	61	Female	Black/African American	Master's	Seeking Employment	MD
P43	Conservative	40	Male	Black/African American	Bachelor's	Employed FT	GA
P40	Liberal	38	Female	White	Bachelor's	Employed PT	MD
P45	Slightly Liberal	25	Male	Asian	Bachelor's	Seeking Employment	DE
P15	Slightly Liberal	21	Female	White	Some College	Student	RI
P29	Liberal	20	Female	White	Some College	Student	DE
P31	Liberal	28	Male	Black/African American	Bachelor's	Employed FT	DE

Table 1. Summary of Interview Participants *(FT = Full Time, PT = Part Time)*

randomly selected and independently coded by both researchers. The initial inter-rater reliability (IRR) of the coding was calculated using Cohen's kappa [103] and resulted in a score of 0.54 on the first randomly selected transcript. The researchers met to resolve disagreements and clarify the codebook's definitions, achieving an IRR of 0.84 ("near-perfect" agreement [24]) in the second coding round with another randomly selected transcript. The remaining transcripts were then split between the two researchers and coded independently. See our Supplementary Materials Note 3 for the complete codebook, including definitions. Refer to Figure 1 for detailed data analysis steps.

4 Findings

Our findings use a cross-data synthesis approach, referencing insights from different data sources to answer the research questions. In this section, we first report on findings from our online survey, mainly focusing on participant demographics and their online news consumption habits. We contrast this with findings from the browsing data collected. We also present results that relate news media literacy and information literacy levels to performance on our headline evaluation tasks. Then, we turn to qualitative insights into people's perceptions of tracking and interventions in online news browsing experiences from our interviews.

4.1 Survey Findings

In all, 34 participants completed the online survey. Results in this section help to contextualize our participant sample. The median age of participants was 27 years old (SD=13.53, Rng=20-67). We outline additional demographics in Table 2 and Table 3 before going into additional detail regarding their perceived internet and computer usage, preferred news outlets, scores on information and news media literacy scales, as well as results from our headline evaluation task. See supplemental material Note 5 for additional participant demographics.

4.1.1 ***Online News Consumption.*** Overall, self-reported news-seeking behaviors varied widely, with the majority reporting that they seek out and read news online at least daily. A full break down can be seen in Table 3 (c).

4.1.2 ***Preferred News Outlets.*** Participants reported visiting well established and widely recognized media outlets across. Self-reported news consumption was measured using a check-all-that-apply question asking participants which news websites (including a write-in option) they visit regularly. The majority of participants self-reported consuming news from The New York Times (58.8%), CNN (38.2%), Washington Post (38.2%), NPR News (26.4%), USA Today (14.7%), Buzzfeed (11.76%), all of which are considered to have left-leaning or liberal editorial stances. We have also noted international news sources such as the BBC (38.2%) and The Guardian (17.64%).

4.1.3 ***News Media Literacy.*** On average, participants demonstrated a relatively high level of news media literacy (i.e., the knowledge and motivations needed to identify, engage with journalism, analyze and evaluate content). The overall news literacy index for the participants, ranging from 0 to 1, was 0.83 (SD=0.10) using a scale described in Vraga *et al.'s* work [115] (Refer to Figure 3).

4.1.4 ***Information Literacy.*** The participant group had a low level of information literacy. The mean score was 0.58 (SD=0.31) on Boh Podgornik *et al.'s* information literacy index [19] (Figure 3). As per the formal definition, this suggests that participants in our sample had a lower level of skill in conducting an efficient search for information, thinking critically about pieces of information, and selecting sources that are high in quality.

4.1.5 ***Headline Evaluations.*** To assess factors influencing participants' judgment and decision-making in the context of online news consumption, we conducted a headline evaluation task where participants evaluated two groups of headlines (true/false) and whether they would share them; see Figure 5 for sample headline news. News accuracy scores range from 0 (no accuracy) to 1 (perfect accuracy). Sharing score also ranges from 0 to 1 (higher values indicate higher likelihood to share). Discernment scores range from -1 (all incorrect responses) to 1 (all correct responses) because they measure ability to distinguish headlines and can take both positive and negative values. On average, the Accuracy Rating (perceived accuracy of the article itself regardless of whether it is chosen to share it or not) given to true news articles is somewhat higher (AR_true = 0.58, SD = 0.15) than to false articles (AR_false = 0.43, SD = 0.19) (Figure 4). Thus, participants rate true articles as more accurate than false articles in the provided sample. Second, in the context of our group, there was a relatively low likelihood of sharing both true and false articles that fell below the mean.

Gender	Count (%)
Female	21 (61.76%)
Male	13 (38.24%)

(a) Gender Distribution

Race	Count (%)
White	16 (47.06%)
Asian	10 (29.41%)
Black or African American	5 (14.71%)
Hispanic or Latino	1 (2.94%)
Prefer not to describe	2 (5.88%)

(b) Race Distribution

Employment	Count (%)
Full time	15 (44.12%)
Part-time	3 (8.82%)
Seeking employment	3 (8.82%)
Student	13 (38.24%)

(c) Employment Distribution

Table 2. Gender, Race, Employment

Political Leaning	Count (%)
Extremely Liberal	1 (2.94%)
Liberal	12 (35.29%)
Slightly Liberal	7 (20.59%)
Moderate	7 (20.59%)
Slightly Conservative	5 (14.71%)
Conservative	2 (5.88%)
ExtremelyConservative	0 (0.00%)

(a) Political Leaning Distribution

Education	Count (%)
Bachelor's Degree	17 (50.00%)
Masters Degree	7 (20.60%)
Doctoral or Professional Degree	4 (11.76%)
Associate Degree	1 (2.94%)
Completed some college but no degree	3 (8.82%)
Post High School Vocational Training	1 (2.94%)
High School Graduate	1 (2.94%)

(b) Education Distribution

News Consumption	Count (%)
Several times an hour	3 (8.82%)
Once an hour	4 (11.76%)
Several times a day	11 (32.35%)
Once a day	5 (14.71%)
Several times a week	6 (17.65%)
Once a week	3 (8.82%)
Several times a month	1 (2.94%)
Never	1 (2.94%)

(c) Online News Consumption

Table 3. Political Leaning, Education, News Consumption

However, true and false articles were equally likely to be shared by individuals (SH_true = 0.22, SD = 0.24, SH_false = 0.23, SD = 0.27) (Figure 7). Hence, content accuracy is not a strong determinant in shaping their sharing behavior. Third, we measured headline discernment. It assesses participants' ability to differentiate between true and false content when deciding what they would share on social media. Participants had a slightly negative score (DI_dis = -0.01, SD = 0.16) for headline sharing discernment indicating people tended to have a bit of difficulty in recognizing credible articles that are worth sharing. However, the mean score for accuracy discernment was positive (DI_acc = 0.15, SD = 0.20) (Figure 6) indicating participants tended to share articles they thought were accurate despite the struggle with discernment. More detailed analysis of these measures in relation to the web logs are presented in the section 4.3.

4.2 Findings | Browsing Data

Having gathered insights from self-reported measures on participants' news consumption habits and media literacy skills, this section examined observed data logs and reports on descriptive statistics computed from our browsing data.

4.2.1 Browsing Time. Participants, on average, engaged with the plugin for nine days throughout the two-week logging period. Overall browsing time, including news browsing, varied greatly among participants, with some being very active and others less so. Sessions were analyzed (similar to [15]) in terms of general browsing and news sessions. To define distinct sessions on a given day, we segmented periods of activity when separated by a gap of 15 minutes or more with no user engagement (e.g., clicks, scrolls, or changes in domain). On average, users engaged in active browsing for approximately 2 hours (SD=1.43) each day. Some had short active browsing periods, lasting as little as 10 minutes (i.e., actively going from page to page rather than dwelling on one Google Doc for several hours) and others for up to 5 hours.

4.2.2 Sessions Logged. Despite self-reported engagement with news, our log analysis suggests their everyday news consumption does not match these perceptions. On average, participants engaged in two non-news sessions per day (SD=0.78) and approximately one news session per day

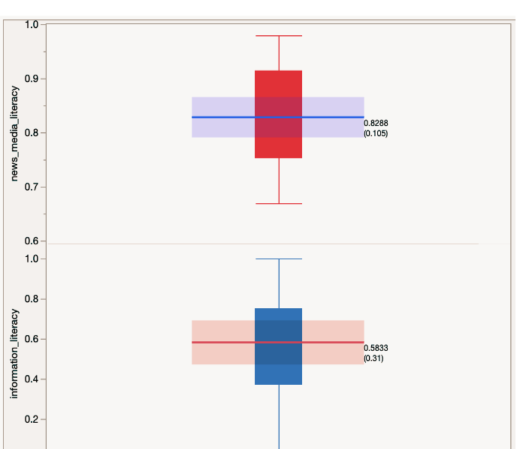


Fig. 3. **News Media Literacy and Information Literacy**: Average score on news media literacy is greater than that of information literacy with less variance.

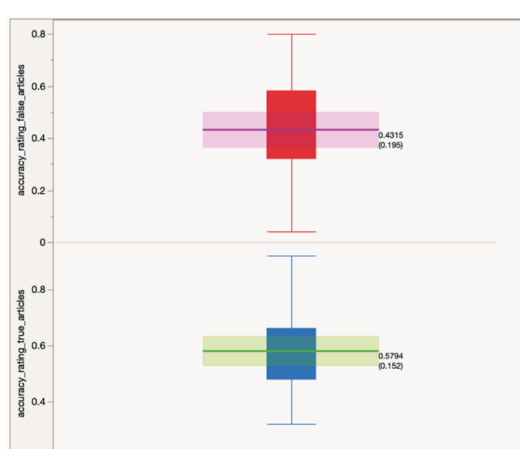
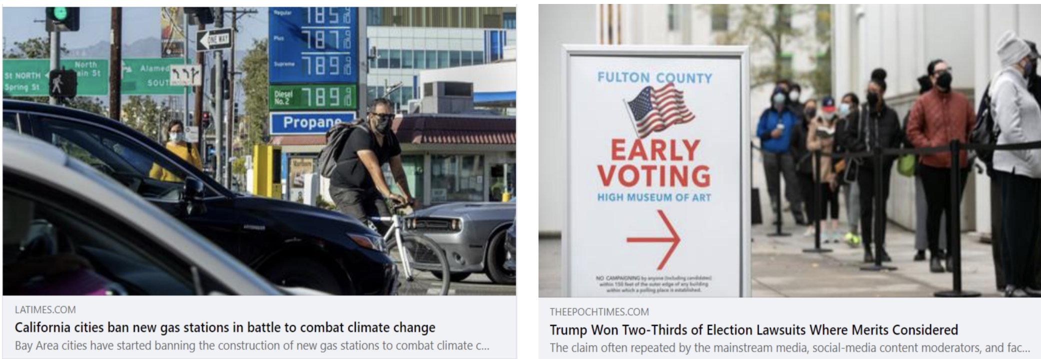


Fig. 4. **Accuracy ratings for articles**: Participants rated the accuracy of different articles on a scale from 1 to 6. The figure displays the distribution of normalized accuracy ratings.



(a) True headline (b) False headline

Fig. 5. **Headline Evaluation Task**: Participants assessed the credibility and trustworthiness of news headlines

(SD=0.55) as illustrated in Figure 8. A "*non-news session*" indicates a browsing session without visits to news websites while a "*news session*" refers to a browsing session where participants interacted with news content by visiting at least one article. In total, we estimate that 17% of browsing sessions were news sessions. Of the 34 participants, 20 recorded news sessions (59%).

4.2.3 News articles, consumption bias, and domain reliability. In news sessions, news reading participants (20/34) collectively consumed 355 articles averaging 17 articles per participant. Our logs also indicate that the majority of articles read by our sample had a *"left center"* bias rating. To determine this, we relied on AllSides' classifications of publishers [8] (left, left center, center, right, and right center) to tag articles and then looked at the dominant content class read by each participant. Most consumed articles with a left-center bias (14, 44.42%) , a few (3, 9.09%) consumed articles with a center bias, two (6.06%) with a left bias, and one (3.03%) with a right bias. Further, we analyzed the reliability of domains of news publishers by cross-comparing our logs with a dataset by Hause *et al.* [64] containing these ratings. Among 84 unique publisher domains visited by our participants, only five were labeled as "unreliable", while the vast majority (79/84) of domains were

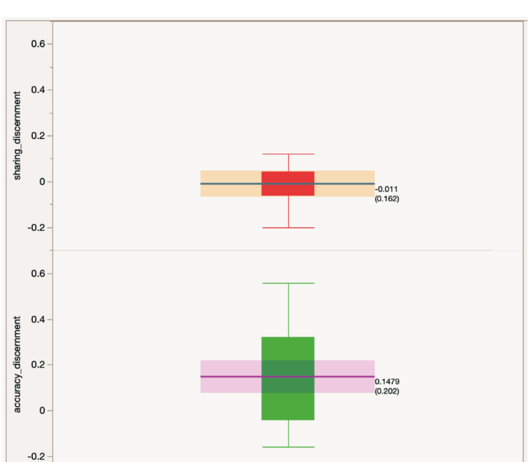


Fig. 6. **Headline Discernment**: Accuracy discernment is greater than that of sharing discernment.

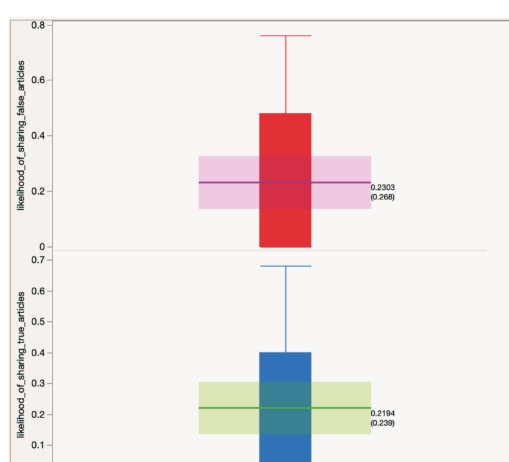


Fig. 7. **Likelihood of sharing**: True and false articles were equally likely to be shared.

labeled as "reliable". These findings support the research by Guess *et al.* [44] and indicate that participants had limited exposure to unreliable publishers known for producing misinformation.

4.2.4 Lateral Reading. Toward addressing one of our primary research questions—*do participants engage in lateral reading in reality when engaging with news*—findings indicate that 16 out of 34 (47%) participants presented evidence of lateral reading, using multiple news sites when engaging with a news article. We defined conditions for tagging instances as lateral reading by focusing on factors like article timestamps (e.g., must be within 5 minutes of each other) and content similarity (e.g., must be a similar topic).

4.3 Findings | Browsing Data and Survey

Our data and findings so far suggest that the more time participants spent online, the more they engaged with news articles of a *"left center"* variety. We also analyzed users' reading behaviors and identified those who exhibited lateral reading behavior. Next, we explore relationships between survey measures and these features (if any). We used different tests, such as the t-test and the Mann-Whitney test, depending on the nature of our data and normality assumptions.

4.3.1 Time Spent Online, News Consumption, and Literacy Scores. According to our log data, users who engaged in more news reading sessions, read more news. Figure 9 shows a strong positive correlation *(r = 0.79)* between the number of "news_sessions" and the corresponding "total_articles" (p = .004). A linear regression analysis was performed to examine the influence of the variable "news_sessions" on the "total_articles". An ANOVA was used to test whether this value was significantly different from zero. It seems to follow that those who engage more frequently with news sessions tend to encounter a higher number of total articles *(R^2 = 0.63, $f(1, 31) = 51.84$, p < .0001*.)* Using our present sample, we also observed, (as seen in Figure 10) a moderate-positive

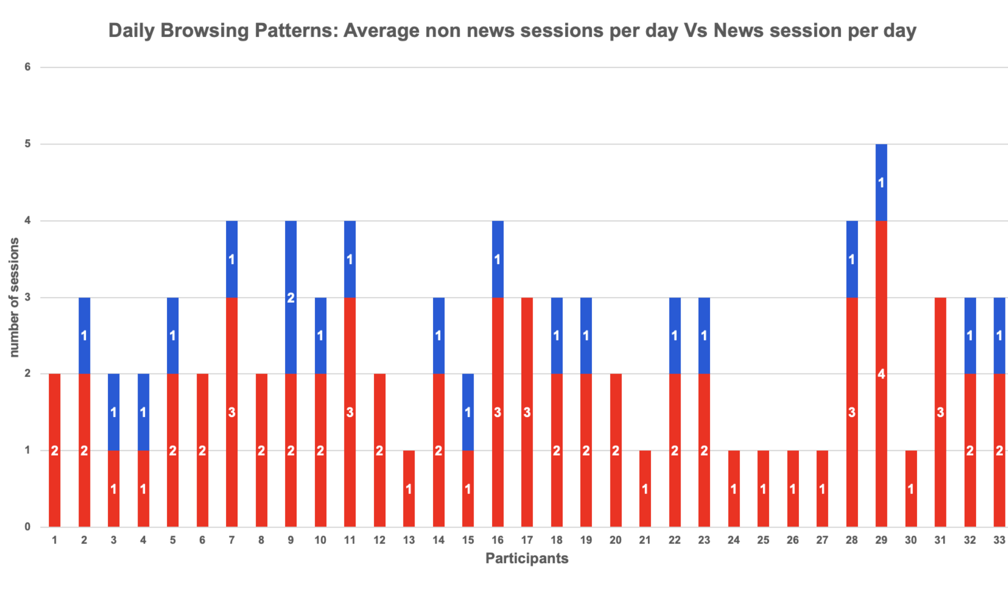


Fig. 8. Participants' Daily Browsing Patterns.

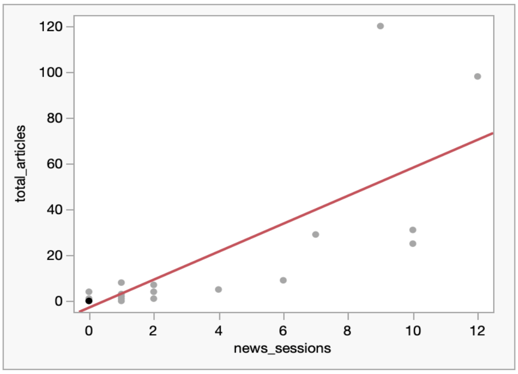


Fig. 9. Articles read and News session

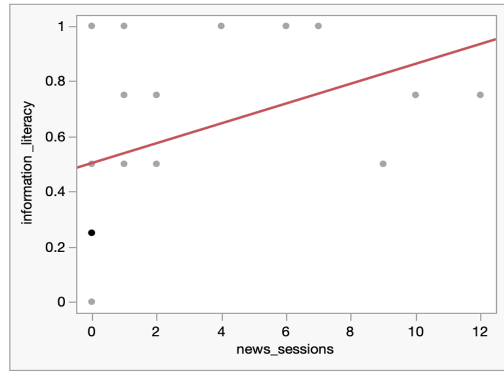


Fig. 10. Information literacy and News session

correlation *(r = 0.4)* between how often individuals engaged with news ("news_sessions") and their information literacy levels (R^2 *= 0.16, f(1, 31) = 5.98, p = 0.02**), but the same was not true for news media literacy levels. Regression indicated that news sessions explained 4.36% of the variance in news media literacy, but this effect was not statistically significant (*F = 1.41, p = .243,* R^2 *= 0.04*).

We also saw a meaningful association and positive correlation (*r > 0.2*) between age and the total number of articles accessed and the interaction with news sessions. Within our sample, older individuals tend to access or read more articles than younger individuals.

4.3.2 Literacy Scores, Information Accuracy, Discernment, and Sharing Behavior. Participants with higher news media literacy scores tend to assign lower accuracy ratings to false articles (*r = -0.43,* R^2 *= 0.18, f(1, 31) = 7.17, p = 0.0117**); see Figure 11. Thus, individuals with better news media literacy skills are more likely to recognize and label false information as inaccurate. They are also better at determining the accuracy of headlines (*r = 0.4,* R^2 *= 0.15, f(1, 31) = 5.6, p = 0.0245**); see Figure 12. However the relationship between news media literacy and accuracy rating of true articles is non-significant (*r = -0.04, p = .845*).

Likewise as news media literacy increases, there is a tendency for the likelihood of sharing of both true and false articles to decrease, and vice versa (*p < .05*). Participants with higher news media literacy are more cautious and discerning in their sharing behaviors, being less likely to share

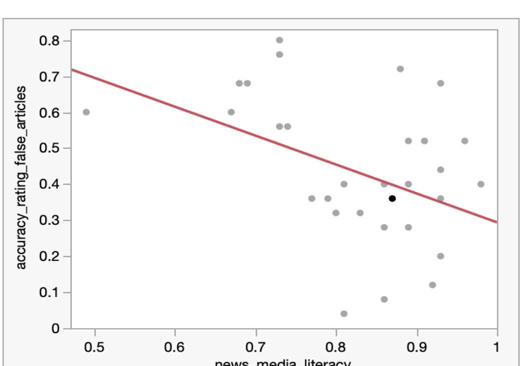


Fig. 11. News media literacy Vs. Accuracy rating of false article

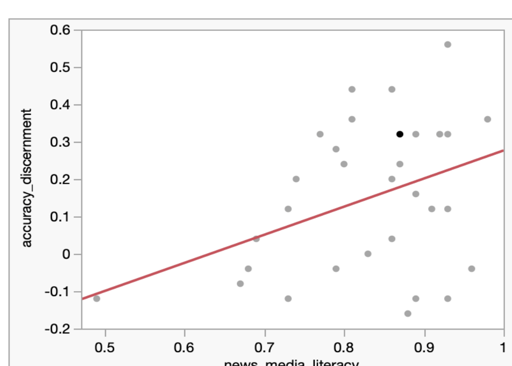


Fig. 12. News Media Literacy Vs. Accuracy Discernment

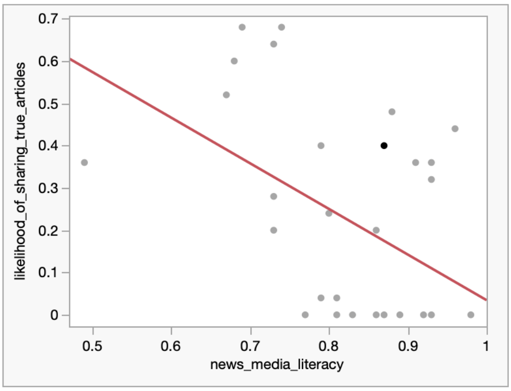


Fig. 13. News media literacy Vs Likelihood of sharing (*True article*)

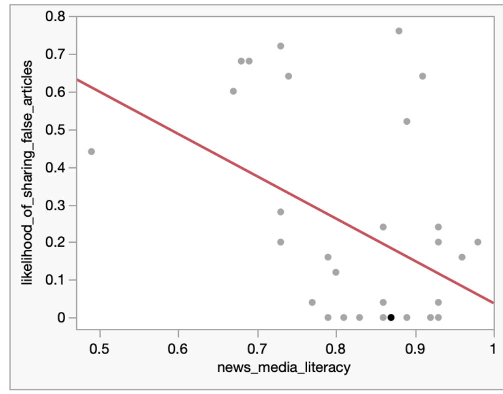


Fig. 14. News Media Literacy Vs Likelihood of sharing (*False article*)

	News Media Literacy (nml)				Information Literacy (inf)			
Dimension	**r**	R^2	**f(1,31)**	**p**	**r**	R^2	**f(1,31)**	**p**
Accuracy Rating of True article	-0.04	0	0.04	0.845	0.1	0.01	0.33	0.565
Accuracy Rating of False article	-0.43	0.18	7.17	0.0117*	-0.5	0.25	10.33	0.0030*
Accuracy Discernment	0.4	0.15	5.6	0.0245*	0.5	0.31	14.13	0.0007*
Likelihood of sharing True article	-0.47	0.22	8.9	0.0054*	-0.5	0.23	9.6	0.0042*
Likelihood of sharing False article	-0.5	0.19	7.4	0.0020*	-0.5	0.24	9.9	0.0035*

Table 4. Summary Statistics for media literacy dimensions, with p-values tested at the 0.05 level.

articles without verifying their accuracy as seen in Figure 13 and Figure 14. In Table 4 the regression values and significance tests for the regression model across all the variables are presented in detail. Check Supplementary Note 4 for similar plots in information literacy. The interpretation of how these measures relate to information literacy is similar to that of news media literacy. For the remaining measures, either there was non-existent relationship or they were statistically insignificant.

4.3.3 Lateral Reading and Average Time Spent Per Day. We also observed that participants who practiced lateral reading spent more time online (*M=2.2 hrs a day actively browsing, SD=88.06*) than those who did not (*M=1.7 hrs a day actively browsing, SD=84.32*) (Figure 15). However, for the given data, Mann-Whitney U-Test showed that the difference between "Yes" and "No" with respect to avg_minutes_per_day, was not statistically significant (*U = 101.5, p = .217, r = 0.22).*

4.3.4 Lateral Reading and News Session. Participants who read laterally more had higher values for the dependent variable number of news_sessions *(M=4, SD=4.06)* than those who did not *(M=1, SD=2.19).* For our given data a Mann-Whitney U-Test showed that the difference between two groups was statistically significant, *(U = 64, p = .009 with a medium effect (r = 0.47)).*

4.3.5 Lateral Reading and Literacy Scores. Participants who demonstrate lateral reading behaviors scored higher on our literacy measures, as illustrated in Figure 16. The results of the descriptive statistics showed that the Lateral reading (Yes) group had higher values for the dependent variable news_media_literacy *(M = 0.87, SD = 0.07)* than the (No) group *(M = 0.79, SD = 0.12).* Similarly, (Yes) group had higher values for information_literacy *(M = 0.7, SD = 0.29)* than the (No) group *(M = 0.47, SD = 0.29).* Levene's Test and the Brown-Forsythe Test, both are used to assess whether two or

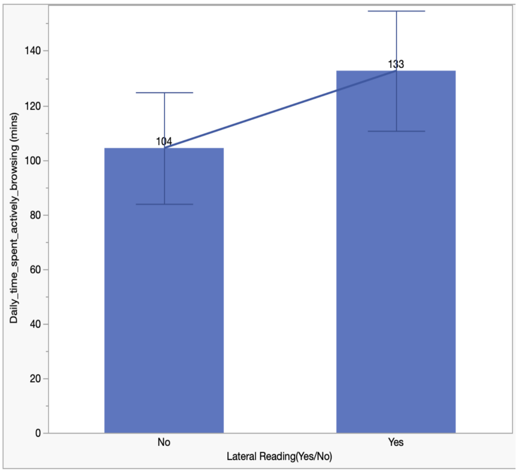


Fig. 15. Lateral reading and Time spent browsing (*mean scores labeled*)

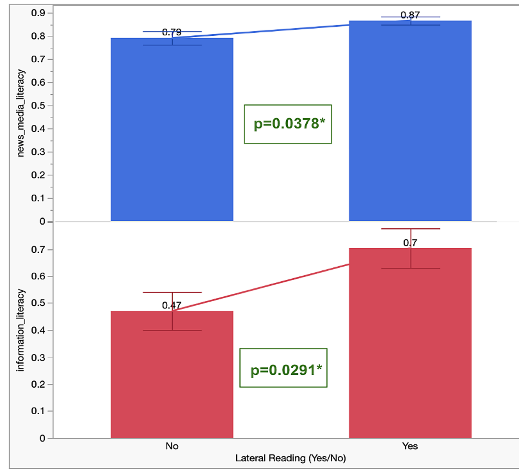


Fig. 16. Lateral reading and Literacy scores (*mean scores labeled*)

more groups have equal variances, which is an important assumption in many statistical tests like the t-test or ANOVA. Our analysis also suggest that our data does not significantly deviate from normality.

A two-tailed t-test for independent samples (equal variances not assumed) showed significant differences in mean scores between the two groups for news_media_literacy (*$t(25.92) = 2.17$, $p = 0.0378^*$, 95% CI [0.01, 0.15]*). Similarly, for information_literacy, the difference between Yes and No (equal variances assumed) was statistically significant *($t(31) = 2.28$, $p = 0.0291^*$, 95% CI [0.03, 0.44])*. The effect size ranges from medium to strong in both cases *(Cohen's $d = 0.77$ to 0.8)*. Given the nature of our p-value, R square and moderate correlation combined with the significant overall test, we consider our results as suggestive and preliminary. We also conducted a residual analysis and verified that our model assumptions were not violated. With all these tests, we want to understand the role of underlying factors rather than using the model to make predictions.

4.4 Interview Findings

To understand how participants online actions align with the data from logs and survey, we conducted a follow-up, semi-structured interviews. During these interviews, 15 participants were asked to reflect on (i) their present behaviors, including their news-seeking habits, over a two-week period and related topics. Additionally, they discussed (ii) perspectives on existing interventions and (iii) offered recommendations for tailoring interventions to better meet their needs.

4.4.1 ***Current Behaviors.*** This section explores participants' browsing habits and perspectives on the challenges of misinformation spread and possible interventions.

News reading and browsing habits. In discussing the time spent online for reading news, interview findings showed a contrast between self-reported frequency of news consumption and observed habits. Most participants (14/15) in our interview acknowledged a daily habit of reading online news articles with an average of 45 minutes per day reading. Seven out of fifteen participants found it challenging to track their reading time due to multitasking and switching tabs. Inconsistent reading patterns across different platforms like websites, apps, and social media further complicated time estimation. Participants also stated that they try to assess the credibility and relevance of the source before deciding how much time and attention to give which allows them to be efficient and maintain control over what they read.

> *"I often struggle to figure out how much time I spend reading articles because I'm quite meticulous about fact-checking. If I read an interesting article, I don't just stop there; I want to see how different news outlets are portraying the same story. So I might go to CNN, Fox, or even MSNBC or PBS to read coverage there, so it's a bit tricky to nail down exactly how long I'm on each article" (P17).*

Second, some did not engage in reading online news regularly, and when they did so, they did it briefly: *"I am clicking on and off pretty fast, but I don't know what the average time is" (P10).*

Sharing habits. Most participants (12/15) admitted to sharing sensational, outlandish and exciting news aligning with their beliefs, primarily for entertainment, regardless of their accuracy. They share such stories with close contacts who share similar views. However, some participants acknowledged efforts to reduce this behavior. For instance, P13 mentioned, *"I try not to share hot-button content anymore. If it's an interesting science article, I might share it, but I never read the comments. I'm just simply reading it, and that's it"*. Participants also shared insights into information overload influences their sharing and discernment behaviour. As P27 stated, *"When I'm overwhelmed by the volume of information, I tend to share less. It feels like I can't keep up, so I become more selective in what I share with others"*.

Fake News Propagation. Before discussing potential solutions to combat misinformation, we asked participants on why misinformation spreads. All 15 participants pointed to confirmation bias and political bias as key factors, often tied to political motivations. For instance, P34 observed, *"those who spread false information force people or lead people to support certain policies"*. While two participants doubted intentional sharing of fake news, others cited reasons such as lack of education (4), failure to critically evaluate sources (4), financial gain (5), or a desire for attention on social media (2). Participants emphasized the need for media literacy to assess information sources and discern motives behind false information.

4.4.2 **Perceptions of Current Interventions.** This section aims to evaluate the effectiveness of current interventions and gather insights to improve them further.

Perceptions of Media Bias ratings. When asked about media bias ratings, a third of participants (5/15) strongly supported the idea by saying it helps them to cross-reference different sources to get a more balanced view while another third had opposing views. P13 expressed frustration, saying, *"I wish there were no biases. I feel the media is heavily biased and I can never be sure if the information I am reading is accurate. It is very frustrating. I worry about perpetuating biased narratives"*. The remaining participants were neutral, believing media bias can be helpful but advocating for reduced bias in publishing.

Perceptions of Personalized Recommendations and Tracking. Over half of participants (10/15) attribute misinformation to personalized recommendation systems, linking it to political polarization. Some (3/15) actively restrict these systems desiring unfiltered news. P13 stated, *"I don't want [news] tailored to me. Just give me everything that's out there and let me decide what I want to look at."* The rest (2) expressed frustration in trying to avoid online tracking enabling personalized recommendations. For example, P41 said,

> *"I tried to disable the privacy settings and cookies but Google and other search engines still seem to know what I am thinking. I don't think I can alter it much. I've reached the point where I won't do anything that requires a complex algorithm and is commercial. I'm going to stop watching YouTube and Netflix. YouTube merely wants to keep you there*

> *while becoming more extreme. I can definitely see how these algorithms lead to political polarization" (P41).*

About half (7/15) find it challenging to find the news they want, while the rest (6/15) believe algorithms effectively suggest relevant articles without any issues. For example, P42 stated, *"No issues with algorithms; they're helpful, and suggest relevant articles I might have missed, saving me time from searching and reading [uninteresting] content."* The remaining (2) stressed the importance of algorithms presenting diverse perspectives. P45 mentioned,

> *"They can show different sides of an issue, making sure each news story includes a right-wing perspective. While not all do, many have an equivalent. For example, CNN is against Fox. I think they should present a variety of viewpoints and let me decide for myself. People have different views on algorithms—some like them for suggesting news, while others want more diversity" (P45).*

Perceptions of Content Warnings. Most participants (12/15) found current interventions like content warnings and fact-checking features helpful in their online news experiences. They recognized content warnings as valuable, especially for graphic or extreme content and news about public health or elections. However, a smaller number of participants (three) found them annoying. Participants mentioned various fact-checking tools, including Twitter prompts, Google Safari pop-ups, Instagram pages, Yahoo website content warnings, and YouTube video warnings. For example, P11 mentioned,

> *"If you read an article about COVID or the COVID vaccine, it might say something like, "Hey, be aware, this is out of date". This news report is based on data from six months ago and may not be up-to-date. Certain YouTube videos I've seen will show a warning that says, Warning: The COVID-19 vaccine is known to be safe. This video presents an opposite viewpoint. You should be aware of the truth" (P11).*

While the rest three mentioned rarely or never encountering content warnings or other interventions while reading articles or browsing the internet. For example, P31 mentioned, *"Yes, I am familiar with content warnings, and I don't usually visit sites where they would be needed".*

Perceptions of Sentiment Analysis and Nudges. Over a third of participants (6/15) support UI based nudges, prompts and subtle reminders for title and content accuracy. However, half knew little about these interventions, unsure of their effectiveness, while others couldn't share an opinion. Regarding sentiment analysis, over half (7/15) found it helpful if trustworthy, with privacy concerns mentioned, with P45 stating,

> *"While sentiment analysis sounds interesting, I worry about the privacy implications but yeah knowing the sentiment would be useful, but it depends on who's evaluating it—AI or a human being. If it's AI, we need to improve it through machine learning. And those nudges might feel intrusive, like someone telling me how to think. I prefer making my own judgments without external influence".*

Similarly, one-third (5/15) were uncertain about the usefulness of sentiment or tone information, with two expressing criticism and skepticism, *"I'm not sure about the article's sentiment or tone, but it might be useful for those unfamiliar with the topic. However, it might also be unhelpful because, you know, who are you to determine what is positive and negative?" (P44).* Participant P44 also suggested a personal informatics dashboard for users to reflect on their activity, assess behavior changes,

> *"It would be excellent to have a feature that allows users to view their activity during the past week, reflect on what they did, and determine whether it has changed their behavior. I'd like to see everyone have access to as much information as possible about the safety,*

> *efficacy, and costs of drugs, vaccines, devices, and medical services, particularly regarding health care. Those who think the content warning is part of a conspiracy would not use it."*

Others proposed increasing filtering options within online publication systems. For example, P23 suggested, *"You could have to filter for far left and far right news media content. So, if that's what you're into, you'd get a mix of perspectives from both extremes..."* Another suggestion from P24 favored redirection rather than completely prohibiting articles that appear to contain misinformation. This participant said,

> *"I would say that instead of outright banning articles that seem like they might be misinformation, include a redirection". For example, if an article discusses COVID-19 and it seems that it's probably unreliable, you could say, "This article may include misinformation about COVID-19; please see the CDC website" (P24).*

Knowledge and Familiarity with News Media Tools. When asked about evaluating sources, participants varied in their fact-checking engagement. While two-thirds (10/15) knew about fact checking websites, most were unfamiliar with similar browser extensions. A few (2/15) occasionally checked information with Snopes but not other sources. Others lacked a fact-checking routine, trusting specific news outlets without verification. P10 mentioned, *"I usually trust the news sources I follow and never felt the need to verify the information they provide"*. This highlights diverse fact-checking approaches, from cautious verification to reliance on trusted sources.

Privacy Concerns with Online Tracking Tools. Opinions on a tool detecting misinformation and tracking online experiences varied on privacy and data tracking. A third (5/15) expressed hesitation due to concerns about constant monitoring. As P30 expressed,

> *"I rarely install plugins unless I believe they are crucial because I am generally wary about data collection. If it monitors my browsing behavior, looks at my news, and gives me feedback, I will not download it. It would be insulting to me personally, and it would also be quite dangerous for many other people" (P30).*

Seven were neutral, seeking clarity on data collection, privacy policies and data protection measures, while two were positive seeing the potential benefits of accurate information about online news publishers. Those neutral wanted clarity on data collection before considering use, as P17 summarized,

> *"I would consider using it if I felt like I was being bombarded with false information and needed a way to verify its accuracy, but I would need more information on its privacy policies and data protection measures before making a decision" (P17).*

Those who were positive saw value in tracking, wanting benefits in return, like P23 said, *"I am comfortable using such tools if they provide me with good articles, and I do not mind sharing my browsing history with anyone, but they should give me something in return"*. A few felt their data wasn't too valuable as P24 noted, *"I do not worry too much because I do not look up anything too crazy on my laptop. I also have a lot of third-party cookies, so they are always collecting my data on Google Chrome and shopping websites, so I am not worried about giving it out voluntarily"*. Overall interview results show diverse opinions, with some positive, some hesitant, and most neutral, seeking benefits for privacy risks.

5 Discussion

Our study's key contribution is a thorough analysis of users' online news consumption behaviors, achieved through a mixed-method approach. By combining quantitative and qualitative methods, we quantified behaviors and looked into the nuanced reasons and contexts behind them. Our ability to improve the validity of our quantitative results from a relatively small sample is supported by previous research [16]. Other similar studies have demonstrated that integrating quantitative data with qualitative insights leverages the respective strengths of each approach by generating more complete data [28, 57]. Therefore, our approach allowed us to identify how perceived and observed behaviors correlate with people's ability to discern information, influencing their news consumption habits. This examination of user habits and patterns forms the basis for understanding how interventions can be effectively designed and implemented.

Here, we address our research questions, discuss discrepancies in users' perceptions of their news browsing habits with their browsing logs, and discuss perceptions of the challenges and benefits of current interventions in news browsing experiences. Finally, we describe a set of design implications for future tools and interventions.

5.1 Understanding Perceptions and Practices in News Consumption

Addressing RQ1, users may perceive themselves as consuming news from diverse sources or spending significant time on news platforms. However, actual behavior analysis might reveal a different pattern and show whether this behavior is consistent and sporadic, such as limited engagement with varied sources or shorter reading times. As seen from our survey and interview findings, this gap in perception and reality is influenced by factors like multitasking and variations in reading intensity. That said, participants tended to visit reliable sources (as seen from section 4.2.3), and their behavior related to lateral reading aligns with what is typically taught in media literacy interventions [116]. Although we did not explicitly inquire about participants' formal training in these methods, they demonstrated awareness of such practices (such as cross-checking and lateral reading). However, responses on surveys and interviews may be influenced by social desirability bias, where individuals portray themselves in a more favorable light, leading to potential discrepancies between stated awareness and actual application [42].

5.2 Discernment Abilities In Online News Credibility Evaluation

To answer RQ2, the relationship between user features, such as literacy levels, and discernment abilities in assessing news credibility is important in determining online information consumption behavior. We observed that participants who engage in lateral reading were less likely to share articles without verifying their accuracy (refer to section 4.3.2). These implications drive practical applications in designing targeted tools and promoting desired online behaviors. For example, integrating quantitative data on users' news website visits and time spent with qualitative insights on trust in news sources can inform effective interventions. We also observed that while information literacy tends to be lower than news media literacy, both are correlated with data collected from surveys and weblogs. Our results partly align with prior research on effectiveness of media literacy interventions [45, 72] but offer a distinctive contribution by exploring the correlation between user features and literacy dimensions that directly affect their online information consumption behavior. Users with advanced literacy not only evaluate news more effectively but also may have developed habits that protect them from misinformation.

On the other hand, contrary to concerns about the prevalence of misinformation [7, 63, 90], our study suggests that interactions with misinformation, such as consuming news from unreliable domains and sharing may be infrequent, supported by our analysis where only few instances of misinformation hits were identified (refer section 4.2.3) and lower sharing likelihood. Despite challenges in discerning truth from falsehood for sharing decisions (comparable to [30, 87]), participants with effective lateral reading habits and higher news media literacy scores demonstrated improved accuracy. The statistically significant, moderate, negative correlation with fake article accuracy ratings indicates that individuals with higher levels of news media literacy are more likely to discern fake news as inaccurate. In contrast, the negligible correlation with true article accuracy ratings suggests that news media literacy has little influence on the perception of true news accuracy.

Hence, media literacy skills are practical in identifying false news, but their impact on recognizing true news is less significant. We emphasize that accurate reporting of true news may lack critical context, highlighting the need for media literacy to focus not only on debunking false information but also on critically analyzing and verifying seemingly true news. Therefore, effective media literacy tools should aim for behavioral change and consistently apply critical evaluation skills.

5.3 User Reactions to News Consumption Interventions

To answer RQ3, participants generally appreciated the concept of tools that might improve their interactions with online news (section 4.4.2). Participants saw value in tracking their news consumption habits and getting assistance with evaluating information during their online interactions. They expressed frustration in navigating diverse news sources, and guidance on publisher bias was viewed as a potential benefit of such tools. However, there was generally low awareness of existing tools or browser plugins that provide such data, highlighting an awareness problem that challenges adoption of such tools.

Participants also had *privacy concerns* around online tracking and the potential for data misuse—particularly as it is easy to forget about as a few participants in our study did. Their views on being tracked were varied and ranged from concern (i.e., not wanting to be tracked) to ambivalence (i.e., everything online already tracks them), though they tended to skew negative. Users may hesitate to use tools requiring access to their browsing data or personal information. Additionally, there were numerous challenges related to *trust in online news systems*, including the perception of media bias, the creation of filter bubbles and echo chambers, and a lack of transparency in recommendation systems (section 4.4.2).

5.4 Design Recommendations

Based on our study, we offer the following design recommendations for developers of online news browsing and intervention tools.

5.4.1 Enhance Browsing with Personal Informatics. As indicated by our interview findings, users may be interested in tracking their news habits to help them stay informed (similar to previous findings [12]). Tools that provide personal informatics may mitigate over and under-estimation of online news consumption by providing individuals with features to self-assess their time spent. This interaction could even be playful, such as a news-tracking extension that prompts users to guess their daily news engagement time and offers feedback to improve accuracy.

Future interventions based on personal informatics should be able to track users' habits (*reading time, the number of articles read, and the dominant bias of the news articles consumed*) and could find ways to display this information back in holistic ways to offer insights via in-situ dashboards. By surfacing data about past activities, users may be motivated to alter their behaviors to interact with news more regularly, consume news from more reliable sources, seek alternative perspectives, and avoid information silos. Interventions along these lines may help users better synthesize what and how they experience online news. However, engaging general audiences versus avid news readers may prove difficult as existing tools had general low awareness in our sample presenting adoption issues.

5.4.2 Integration of the Lateral Reading Tools. The effectiveness of lateral reading—a strategy encouraged to verify the credibility of online sources—is contingent upon individuals' digital literacy levels and cognitive abilities [116]. As seen from our study, while half of the users adeptly employ lateral reading to discern trustworthy information, others may struggle due to cognitive overload or insufficient digital literacy skills. Also lateral reading and fact-checking typically correlates with higher literacy levels, higher online engagement, frequent reading habits and a better ability to evaluate the reliability of news sources (section 4.3). Thus, browser-based interventions that are aimed at improving lateral reading skills could benefit from leveraging data from users who excel in these techniques. This approach would also help less proficient users find appropriate complementary content (similar to collaborative filtering methods [36, 65]). Further, within news articles, integrating links to additional articles within the current reading eases lateral reading [116], particularly if users' behavior devolves to accessing only a subset of perspectives.

5.4.3 Optimizing Media Literacy. Based on the link observed between media literacy and rating article headlines, future tools could offer personalized challenges and feedback tailored to users' performance in assessing news article accuracy to help them identify misleading information and reduce potential negative interactions. Since participants appreciate visual information and interactive features, progress trackers can be embedded that shows users' improvement in news literacy over time based on these assessments. Use visuals or animations to display how their skills develop as they use the intervention to encourage them to keep learning and improve their skills. Given the weak correlation between news sessions, media literacy (section 4.3.1) and sharing likelihood of true and false articles (section 4.3.3), interventions should focus on empowering users more to critically evaluate information and consumer news from diverse sources rather than just increasing news engagement. Future efforts should also consider that not everyone is equally affected. Vulnerable groups, like those with low information literacy or unaware of lateral reading as seen in our study, need special attention (e.g., if people tend to consume unreliable news, the browser could provide a tutorial on identifying these sources). The inclusion of individuals with lower levels of media literacy in the iterative design and evaluation process of the interventions is essential.

5.4.4 Reflective Prompts for User Engagement. To address users' limited exposure to diverse perspectives, as evident from their browsing logs dominated by left-biased news articles, interventions can offer adaptive features based on browsing patterns. These features encourage verification. Research suggests that incorporating simple nudges and prompts, such as reminders to emphasize accuracy [91] can incentivize active user participation and promote healthy news consumption [17, 34]. However, reflective prompts in online news consumption, rooted in self-reflection principles, are less explored because they require active self-reflection on people's biases and habits. Given participants' feedback about not wanting to be overwhelmed, we propose integrating brief reflective prompts, periodic reminders, weekly summaries alongside behavioral nudges [55, 113] directly into the online news consumption process as in-situ news reading interventions that does not distract them from their primary online activities.

5.4.5 Non-Intrusive Practices. Our study found that though users were willing to contribute their data for altruistic reasons such as improving online communities and similar to how people track activities to record personal habits [26], participants had concerns regarding current online data collection practices. Based on our qualitative results, installation and setup materials with clear explanations of browser permissions will likely build user trust with these systems. Participant unfamiliarity with plugins and existing tools in interviews implies that clear, well-designed tools with transparency and privacy controls may improve adoption and usage. A gradual exposure approach may build user trust in initial interventions. Intervention tools can start with gentle nudges or subtle reminders, allowing users to become familiar. Features should also balance effectiveness and non-intrusiveness, allowing users to customize and control their experience, like potentially allowing users to choose the frequency or intensity of the intervention or opt for specific types of content to be highlighted or flagged (similar to other browser-based intervention systems like HabitLab [60, 61] and Home Sweet Office [108]).

5.4.6 In-situ Warnings on Content Quality and Standards. Based on user responses, posted warnings on online news content in exceptional situations (such as articles with false claims, biases, framing, inflammatory language, emotional manipulation, sensationalism) are viewed positively. However, these may not always be accurate or run the risk of being overused and ignored. They also risk missing other opportunities to assist users with understanding online news content. One such possibility is the implementation of alternative interventions that can detect sentiments, such as emotionally charged words within articles, and visually highlight relevant sections. The purpose is to draw the reader's attention to those sections and the corresponding correction *in situ* rather than simply posting a warning before the user has even engaged with the content. Improvised in-situ warning methods, if designed right, might offer solutions to "backfire effects" in news consumption intervention work [38, 69].

5.5 Future work and Limitations

While our pilot study, conducted with a convenient sample of participants offers an empirical foundation for examining how users interact with online news media and misinformation, it is important to acknowledge certain limitations in our work. As our study is largely exploratory, the results should be interpreted cautiously. Our findings are not generalizable due to the small sample size and a skewed demographic composition that leans toward highly educated liberal women with a left or left-center bias. Second, and related to the previous point, our study focuses on the (natural) sub-population of active news consumers. Therefore, its findings may not apply to those who have limited exposure to news, mainly through online news platforms. Additionally, in analyzing user experiences, it is imperative to recognize potential biases in participant responses, such as social desirability bias and survey response biases stemming from question framing.

With respect to technical limitations, our study's data collection was limited to participants who installed our Chrome extension on their personal computers to read news, which provides a unique insight into their browsing behavior on that device but does not collect data from others (e.g., smartphones, work computers). We also acknowledge the limitations of the AllSides dataset, which more than likely does not fully capture all content publishers (instead focusing on the largest or most common) and may itself be biased in terms of its rating of publisher bias. Nevertheless, our preliminary results and the trends we observed are interesting in corroborating that users' self-reported news consumption habits often diverge from their observed online behavior and that literacy levels influence users' ability to discern new headline credibility. Future work can verify these results by conducting larger studies with a more diverse sample and evaluating future news interface support tools for their impact on online developing news media literacy skills in users.

6 Conclusion

The objective of our study is to explore how users engage with online news platforms and leverage these insights to design interventions that mitigate the spread of misinformation. We conducted a formative study on the news browsing behaviors of 34 participants, using surveys, log data, and interviews. Our findings indicate that higher media literacy and lateral reading habits are linked to frequent and active news engagement and misinformation detection. Further, individuals' attitudes toward online monitoring and interventions should be carefully considered in developing online platforms and support tools. Users prefer transparent methods to counter misinformation over interacting with hidden decision-makers and recommendation systems. This emphasis on transparency highlights an important concern that should be considered when aiming to create ethical and empowering online environments in this and similar contexts.

Our study advances CSCW works by integrating behavioral insights (i.e., formative user behaviors and interactions in online news environment) with qualitative data and self-reported behaviors. This offers foundational knowledge for designing user-focused interventions and to improve users' ability to discern misinformation. Moreover, our research emphasizes that, while managing misinformation threats is crucial, addressing how we can respond effectively to this content and designing acceptable interventions that make users more resilient is equally important. Our limitations include reliance on computer-based data and skewed demographic distribution. Nevertheless, our insights into individuals' browsing behavior and the associated challenges and opportunities inform design guidelines and practical implications for future work on systems and interventions in online news experiences.

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References

[1] Factcheck.org. 2024. Available at: https://www.factcheck.org/. Accessed: 2024-07-07.
[2] Flipfeed. Available at: https://www.media.mit.edu/projects/flipfeed/overview/. Accessed: 2023-06-12.
[3] NewsGuard. 2024. Available at: https://www.newsguardtech.com/how-it-works/. Accessed: 2024-07-07.
[4] Poynter Institute Politifact.com. 2020. Available at: http://www.politifact.com. Accessed: 2024-07-07.
[5] Snopes Media Group Inc. Snopes.com. 1995. Available at: https://www.snopes.com/. Accessed: 2024-07-07.
[6] WSJ Graphics. 2024. Available at: https://graphics.wsj.com/blue-feed-red-feed/. Accessed: 2024-01-17.
[7] Hunt Allcott and Matthew Gentzkow. 2017. Social media and fake news in the 2016 election. *Journal of economic perspectives* 31, 2 (2017), 211–236. https://doi.org/10.1257/jep.31.2.211
[8] LLC AllSides. 2022. AllSides Media Bias Ratings.
[9] Malik Almaliki. 2019. Online Misinformation Spread: A Systematic Literature Map. In *Proceedings of the 2019 3rd International Conference on Information System and Data Mining* (Houston, TX, USA) *(ICISDM '19)*. Association for Computing Machinery, New York, NY, USA, 171–178. https://doi.org/10.1145/3325917.3325938
[10] Kevin Aslett, Andrew M Guess, Richard Bonneau, Jonathan Nagler, and Joshua A Tucker. 2022. News credibility labels have limited average effects on news diet quality and fail to reduce misperceptions. *Science advances* 8, 18 (2022), eabl3844. https://doi.org/10.1126/sciadv.abl3844
[11] Marianne Aubin Le Quéré, Ting-Wei Chiang, Karen Levy, and Mor Naaman. 2022. Information Needs of Essential Workers During the COVID-19 Pandemic. *Proc. ACM Hum.-Comput. Interact.* 6, CSCW2, Article 306 (nov 2022), 19 pages. https://doi.org/10.1145/3555197

[12] Marianne Aubin Le Quéré, Lauren Tran, Andrew Berger, Christopher Nguyen, Rohini Venkatesan, Yuanhang Xu, Anastasia Sorokina, and Mor Naaman. 2024. An Article a Day: Towards Personal Informatics for Healthy News Consumption. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems (CHI EA '24)*. Association for Computing Machinery, New York, NY, USA, Article 39, 9 pages. https://doi.org/10.1145/3613905.3650854

[13] Michael Barthel, Amy Mitchell, Dorene Asare-Marfo, Courtney Kennedy, and Kirsten Worden. 2020. Measuring news consumption in a digital era. *Washington, DC: Pew Research Center* (2020). https://www.pewresearch.org/

[14] Michael Barthel, Amy Mitchell, and Jesse Holcomb. 2016. Many Americans believe fake news is sowing confusion. (2016). https://www.pewresearch.org/

[15] Frank Bentley, Katie Quehl, Jordan Wirfs-Brock, and Melissa Bica. 2019. Understanding Online News Behaviors. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–11. https://doi.org/10.1145/3290605.3300820

[16] Angelika Bernsteiner, Thomas Schubatzky, and Claudia Haagen-Schützenhöfer. 2023. Misinformation as a societal problem in times of crisis: A mixed-methods study with future teachers to promote a critical attitude towards information. *Sustainability* 15, 10 (2023), 8161. https://doi.org/10.3390/su15108161

[17] Md Momen Bhuiyan, Michael Horning, Sang Won Lee, and Tanushree Mitra. 2021. NudgeCred: Supporting News Credibility Assessment on Social Media Through Nudges. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW2, Article 427 (oct 2021), 30 pages. https://doi.org/10.1145/3479571

[18] Md Momen Bhuiyan, Kexin Zhang, Kelsey Vick, Michael A. Horning, and Tanushree Mitra. 2018. FeedReflect: A Tool for Nudging Users to Assess News Credibility on Twitter. In *Companion of the 2018 ACM Conference on Computer Supported Cooperative Work and Social Computing* (Jersey City, NJ, USA) *(CSCW '18 Companion)*. Association for Computing Machinery, New York, NY, USA, 205–208. https://doi.org/10.1145/3272973.3274056

[19] Bojana Boh Podgornik, Danica Dolničar, Andrej Šorgo, and Tomaž Bartol. 2016. Development, testing, and validation of an information literacy test (ILT) for higher education. *Journal of the association for Information Science and Technology* 67, 10 (2016), 2420–2436. https://doi.org/10.1002/asi.23586

[20] Adrian MP Braşoveanu and Răzvan Andonie. 2019. Semantic fake news detection: a machine learning perspective. In *Advances in Computational Intelligence: 15th International Work-Conference on Artificial Neural Networks, IWANN 2019, Gran Canaria, Spain, June 12-14, 2019, Proceedings, Part I 15*. Springer, 656–667. https://doi.org/10.1007/978-3-030-20521-8_54

[21] Virginia Braun and Victoria Clarke. 2006. Using thematic analysis in psychology. *Qualitative Research in Psychology* 3, 2 (2006), 77–101. https://doi.org/10.1191/1478088706qp063oa

[22] Ceren Budak, Divyakant Agrawal, and Amr El Abbadi. 2011. Limiting the spread of misinformation in social networks. In *Proceedings of the 20th International Conference on World Wide Web* (Hyderabad, India) *(WWW '11)*. Association for Computing Machinery, New York, NY, USA, 665–674. https://doi.org/10.1145/1963405.1963499

[23] Joanna M Burkhardt. 2017. History of fake news. *Library Technology Reports* 53, 8 (2017), 5–9.

[24] John L Campbell, Charles Quincy, Jordan Osserman, and Ove K Pedersen. 2013. Coding in-depth semistructured interviews: Problems of unitization and intercoder reliability and agreement. *Sociological methods & research* 42, 3 (2013), 294–320. https://doi.org/10.1177/0049124113500475

[25] Xinran Chen and Sei-Ching Joanna Sin. 2013. 'Misinformation? What of it?'Motivations and individual differences in misinformation sharing on social media. *Proceedings of the American Society for Information Science and Technology* 50, 1 (2013), 1–4. https://doi.org/10.1002/meet.14505001102

[26] Eun Kyoung Choe, Nicole B. Lee, Bongshin Lee, Wanda Pratt, and Julie A. Kientz. 2014. Understanding quantified-selfers' practices in collecting and exploring personal data. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Toronto, Ontario, Canada) *(CHI '14)*. Association for Computing Machinery, New York, NY, USA, 1143–1152. https://doi.org/10.1145/2556288.2557372

[27] John W Creswell. 1999. Mixed-method research: Introduction and application. In *Handbook of educational policy*. Elsevier, 455–472. https://doi.org/10.1016/B978-012174698-8/50045-X

[28] John W Creswell and Vicki L Plano Clark. 2017. *Designing and conducting mixed methods research*. Sage publications. https://doi.org/10.1111/j.1753-6405.2007.00096.x

[29] Homero Gil De Zúñiga, Manuel Goyanes, and Chris Skurka. 2023. Understanding Fake News Corrective Action: A Mixed-Method Approach. *International Journal of Communication* 17 (2023), 3428–3450. Available at http://ijoc.org.

[30] Ziv Epstein, Nathaniel Sirlin, Antonio Arechar, Gordon Pennycook, and David Rand. 2023. The social media context interferes with truth discernment. *Science Advances* 9, 9 (2023), eabo6169. https://doi.org/10.1126/sciadv.abo6169

[31] Craig Silverman et al. 2016. Hyperpartisan Facebook pages are publishing false and misleading information at an alarming rate, BuzzFeed News. *Available at: https://www.buzzfeednews.com/article/craigsilverman/partisan-fb-pages-analysis.kaJBYd4a8* (2016).

[32] Seth Flaxman, Sharad Goel, and Justin M Rao. 2016. Filter bubbles, echo chambers, and online news consumption. *Public opinion quarterly* 80, S1 (2016), 298–320. https://doi.org/10.1093/poq/nfw006

[33] Martin Flintham, Christian Karner, Khaled Bachour, Helen Creswick, Neha Gupta, and Stuart Moran. 2018. Falling for Fake News: Investigating the Consumption of News via Social Media. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) *(CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–10. https://doi.org/10.1145/3173574.3173950

[34] BJ Fogg. 2009. A behavior model for persuasive design. In *Proceedings of the 4th International Conference on Persuasive Technology* (Claremont, California, USA) *(Persuasive '09)*. Association for Computing Machinery, New York, NY, USA, Article 40, 7 pages. https://doi.org/10.1145/1541948.1541999

[35] Herbert J Gans. 2004. *Democracy and the News*. Oxford University Press on Demand.

[36] Florent Garcin, Kai Zhou, Boi Faltings, and Vincent Schickel. 2012. Personalized News Recommendation Based on Collaborative Filtering. In *2012 IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology*, Vol. 1. 437–441. https://doi.org/10.1109/WI-IAT.2012.95

[37] Kiran Garimella, Tim Smith, Rebecca Weiss, and Robert West. 2021. Political polarization in online news consumption. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 15. 152–162. https://doi.org/10.1609/icwsm.v15i1.18049

[38] R. Kelly Garrett and Brian E. Weeks. 2013. The promise and peril of real-time corrections to political misperceptions. In *Proceedings of the 2013 Conference on Computer Supported Cooperative Work* (San Antonio, Texas, USA) *(CSCW '13)*. Association for Computing Machinery, New York, NY, USA, 1047–1058. https://doi.org/10.1145/2441776.2441895

[39] Axel Gelfert. 2018. Fake news: A definition. *Informal logic* 38, 1 (2018), 84–117. https://doi.org/10.22329/il.v38i1.5068

[40] Jennifer Golbeck, Matthew Mauriello, Brooke Auxier, Keval H Bhanushali, Christopher Bonk, Mohamed Amine Bouzaghrane, Cody Buntain, Riya Chanduka, Paul Cheakalos, Jennine B Everett, et al. 2018. Fake news vs satire: A dataset and analysis. In *Proceedings of the 10th ACM Conference on Web Science*. 17–21. https://doi.org/10.1145/3201064.3201100

[41] Nir Grinberg, Kenneth Joseph, Lisa Friedland, Briony Swire-Thompson, and David Lazer. 2019. Fake news on Twitter during the 2016 US presidential election. *Science* 363, 6425 (2019), 374–378. https://doi.org/10.1126/science.aau2706

[42] Andrew Guess, Kevin Munger, Jonathan Nagler, and Joshua Tucker. 2019. How accurate are survey responses on social media and politics? *Political Communication* 36, 2 (2019), 241–258. https://doi.org/10.1080/10584609.2018.1504840

[43] Andrew Guess, Jonathan Nagler, and Joshua Tucker. 2019. Less than you think: Prevalence and predictors of fake news dissemination on Facebook. *Science advances* 5, 1 (2019), eaau4586. https://doi.org/10.1126/sciadv.aau4586

[44] Andrew Guess, Brendan Nyhan, and Jason Reifler. 2018. Selective exposure to misinformation: Evidence from the consumption of fake news during the 2016 US presidential campaign. (2018). https://api.semanticscholar.org/CorpusID:158536258

[45] Andrew M Guess, Michael Lerner, Benjamin Lyons, Jacob M Montgomery, Brendan Nyhan, Jason Reifler, and Neelanjan Sircar. 2020. A digital media literacy intervention increases discernment between mainstream and false news in the United States and India. *Proceedings of the National Academy of Sciences* 117, 27 (2020), 15536–15545. https://doi.org/10.1073/pnas.1920498117

[46] Andrew M Guess, Brendan Nyhan, and Jason Reifler. 2020. Exposure to untrustworthy websites in the 2016 US election. *Nature human behaviour* 4, 5 (2020), 472–480. https://doi.org/10.1038/s41562-020-0833-x

[47] Greg Guest, Arwen Bunce, and Laura Johnson. 2006. How many interviews are enough? An experiment with data saturation and variability. *Field methods* 18, 1 (2006), 59–82. https://doi.org/10.1177/1525822X05279903

[48] Steffen Haesler, Stefka Schmid, and Christian Reuter. 2020. Crisis volunteering nerds: Three months after COVID-19 hackathon# WirVsVirus. In *22nd International Conference on Human-Computer Interaction with Mobile Devices and Services*. 1–5. https://doi.org/10.1145/3406324.3424584

[49] Saqib Hakak, Mamoun Alazab, Suleman Khan, Thippa Reddy Gadekallu, Praveen Kumar Reddy Maddikunta, and Wazir Zada Khan. 2021. An ensemble machine learning approach through effective feature extraction to classify fake news. *Future Generation Computer Systems* 117 (2021), 47–58. https://doi.org/10.1016/j.future.2020.11.022

[50] Hans W. A. Hanley, Deepak Kumar, and Zakir Durumeric. 2023. A Golden Age: Conspiracy Theories' Relationship with Misinformation Outlets, News Media, and the Wider Internet. *Proc. ACM Hum.-Comput. Interact.* 7, CSCW2, Article 252 (oct 2023), 33 pages. https://doi.org/10.1145/3610043

[51] Katrin Hartwig, Frederic Doell, and Christian Reuter. 2024. The Landscape of User-centered Misinformation Interventions - A Systematic Literature Review. *ACM Comput. Surv.* (jun 2024). https://doi.org/10.1145/3674724 Just Accepted.

[52] Monique Hennink and Bonnie N Kaiser. 2022. Sample sizes for saturation in qualitative research: A systematic review of empirical tests. *Social science & medicine* 292 (2022), 114523. https://doi.org/10.1016/j.socscimed.2021.114523

[53] John B Horrigan. 2016. Digital Readiness Gaps. *Pew Research Center* (2016). https://www.pewresearch.org/

[54] Paul T Jaeger and Natalie Greene Taylor. 2021. Arsenals of lifelong information literacy: Educating users to navigate political and current events information in world of ever-evolving misinformation. *The Library Quarterly* 91, 1 (2021), 19–31. https://doi.org/10.1086/711632

[55] Farnaz Jahanbakhsh, Amy X. Zhang, Adam J. Berinsky, Gordon Pennycook, David G. Rand, and David R. Karger. 2021. Exploring Lightweight Interventions at Posting Time to Reduce the Sharing of Misinformation on Social Media. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW1, Article 18 (apr 2021), 42 pages. https://doi.org/10.1145/3449092

[56] Farnaz Jahanbakhsh, Amy X. Zhang, and David R. Karger. 2022. Leveraging Structured Trusted-Peer Assessments to Combat Misinformation. *Proc. ACM Hum.-Comput. Interact.* 6, CSCW2, Article 524 (nov 2022), 40 pages. https://doi.org/10.1145/3555637

[57] Todd D Jick. 1979. Mixing qualitative and quantitative methods: Triangulation in action. *Administrative science quarterly* 24, 4 (1979), 602–611. https://doi.org/10.2307/2392366

[58] Jan Kirchner and Christian Reuter. 2020. Countering Fake News: A Comparison of Possible Solutions Regarding User Acceptance and Effectiveness. *Proc. ACM Hum.-Comput. Interact.* 4, CSCW2, Article 140 (oct 2020), 27 pages. https://doi.org/10.1145/3415211

[59] Tobias Konitzer, Jennifer Allen, Stephanie Eckman, Baird Howland, Markus Mobius, David Rothschild, and Duncan J Watts. 2021. Comparing estimates of news consumption from survey and passively collected behavioral data. *Public Opinion Quarterly* 85, S1 (2021), 347–370. https://doi.org/10.1093/poq/nfab023

[60] Geza Kovacs, Drew Mylander Gregory, Zilin Ma, Zhengxuan Wu, Golrokh Emami, Jacob Ray, and Michael S. Bernstein. 2019. Conservation of Procrastination: Do Productivity Interventions Save Time Or Just Redistribute It?. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3290605.3300560

[61] Geza Kovacs, Zhengxuan Wu, and Michael S. Bernstein. 2018. Rotating Online Behavior Change Interventions Increases Effectiveness But Also Increases Attrition. *Proc. ACM Hum.-Comput. Interact.* 2, CSCW, Article 95 (nov 2018), 25 pages. https://doi.org/10.1145/3274364

[62] Nieman Lab. 2018. Here's How Much Americans Trust 38 Major News Organizations (Hint: Not All That Much). *Nieman Lab* (2018). https://www.niemanlab.org/2018/10/heres-how-much-americans-trust-38-major-news-organizations-hint-not-all-that-much/

[63] David MJ Lazer, Matthew A Baum, Yochai Benkler, Adam J Berinsky, Kelly M Greenhill, Filippo Menczer, Miriam J Metzger, Brendan Nyhan, Gordon Pennycook, David Rothschild, et al. 2018. The science of fake news. *Science* 359, 6380 (2018), 1094–1096. https://doi.org/10.1126/science.aao2998

[64] Hause Lin, Jana Lasser, Stephan Lewandowsky, Rocky Cole, Andrew Gully, David G Rand, and Gordon Pennycook. 2023. High level of correspondence across different news domain quality rating sets. *PNAS nexus* 2, 9 (2023), pgad286. https://doi.org/10.1093/pnasnexus/pgad286

[65] Zhongqi Lu, Zhicheng Dou, Jianxun Lian, Xing Xie, and Qiang Yang. 2015. Content-based collaborative filtering for news topic recommendation. In *Proceedings of the AAAI conference on artificial intelligence*, Vol. 29. https://doi.org/10.1609/aaai.v29i1.9183

[66] Zhuoran Lu, Patrick Li, Weilong Wang, and Ming Yin. 2022. The Effects of AI-based Credibility Indicators on the Detection and Spread of Misinformation under Social Influence. *Proc. ACM Hum.-Comput. Interact.* 6, CSCW2, Article 461 (nov 2022), 27 pages. https://doi.org/10.1145/3555562

[67] Duggan M. 2014. Online harassment: Pew Research Center. https://www.pewresearch.org/internet/2014/10/22/online-harassment/.

[68] Adam Maksl, Seth Ashley, and Stephanie Craft. 2015. Measuring news media literacy. *Journal of Media Literacy Education* 6, 3 (2015), 29–45. https://doi.org/10.23860/jmle-6-3-3

[69] Paul Mena. 2020. Cleaning up social media: The effect of warning labels on likelihood of sharing false news on Facebook. *Policy & internet* 12, 2 (2020), 165–183. https://doi.org/10.1002/poi3.214

[70] Judith Möller, Robbert Nicolai van de Velde, Lisa Merten, and Cornelius Puschmann. 2020. Explaining online news engagement based on browsing behavior: Creatures of habit? *Social Science Computer Review* 38, 5 (2020), 616–632. https://doi.org/10.1177/0894439319828012

[71] Federico Monti, Fabrizio Frasca, Davide Eynard, Damon Mannion, and Michael M Bronstein. 2019. Fake news detection on social media using geometric deep learning. (2019). https://doi.org/10.48550/arXiv.1902.06673

[72] Ryan C Moore and Jeffrey T Hancock. 2022. A digital media literacy intervention for older adults improves resilience to fake news. *Scientific reports* 12, 1 (2022), 6008. https://doi.org/10.1038/s41598-022-08437-0

[73] Mohsen Mosleh, Cameron Martel, Dean Eckles, and David Rand. 2021. Perverse Downstream Consequences of Debunking: Being Corrected by Another User for Posting False Political News Increases Subsequent Sharing of Low Quality, Partisan, and Toxic Content in a Twitter Field Experiment. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 182, 13 pages. https://doi.org/10.1145/3411764.3445642

[74] Rachel R Mourão and Craig T Robertson. 2019. Fake news as discursive integration: An analysis of sites that publish false, misleading, hyperpartisan and sensational information. *Journalism studies* 20, 14 (2019), 2077–2095. https://doi.org/10.1080/1461670X.2019.1566871

[75] Tyler WS Nagel. 2022. Measuring Fake News Acumen Using a News Media Literacy Instrument. *Journal of Media Literacy Education* 14, 1 (2022), 29–42. https://doi.org/10.23860/JMLE-2022-14-1-3

[76] Ruchi Ookalkar, Kolli Vishal Reddy, and Eric Gilbert. 2019. Pop: Bursting News Filter Bubbles on Twitter Through Diverse Exposure. In *Companion Publication of the 2019 Conference on Computer Supported Cooperative Work and Social Computing* (Austin, TX, USA) *(CSCW '19 Companion)*. Association for Computing Machinery, New York, NY, USA, 18–22. https://doi.org/10.1145/3311957.3359513

[77] Emmanouil Papadogiannakis, Panagiotis Papadopoulos, Evangelos P. Markatos, and Nicolas Kourtellis. 2023. Who Funds Misinformation? A Systematic Analysis of the Ad-related Profit Routines of Fake News Sites. In *Proceedings of the ACM Web Conference 2023* (Austin, TX, USA) *(WWW '23)*. Association for Computing Machinery, New York, NY, USA, 2765–2776. https://doi.org/10.1145/3543507.3583443

[78] Eli Pariser. 2011. *The filter bubble: How the new personalized web is changing what we read and how we think.* Penguin. https://api.semanticscholar.org/CorpusID:106656450

[79] Chang Sup Park. 2019. Does too much news on social media discourage news seeking? Mediating role of news efficacy between perceived news overload and news avoidance on social media. *Social Media+ Society* 5, 3 (2019), 2056305119872956. https://doi.org/10.1177/2056305119872956

[80] Jae Hong Park, Bin Gu, Alvin Chung Man Leung, and Prabhudev Konana. 2014. An investigation of information sharing and seeking behaviors in online investment communities. *Computers in Human Behavior* 31 (2014), 1–12. https://doi.org/10.1016/j.chb.2013.10.002

[81] Douglas A Parry, Brittany I Davidson, Craig JR Sewall, Jacob T Fisher, Hannah Mieczkowski, and Daniel S Quintana. 2021. A systematic review and meta-analysis of discrepancies between logged and self-reported digital media use. *Nature Human Behaviour* 5, 11 (2021), 1535–1547. https://doi.org/10.1038/s41562-021-01117-5

[82] Demetris Paschalides, Alexandros Kornilakis, Chrysovalantis Christodoulou, Rafael Andreou, George Pallis, Marios Dikaiakos, and Evangelos Markatos. 2019. Check-It: A plugin for Detecting and Reducing the Spread of Fake News and Misinformation on the Web. In *IEEE/WIC/ACM International Conference on Web Intelligence* (Thessaloniki, Greece) *(WI '19)*. Association for Computing Machinery, New York, NY, USA, 298–302. https://doi.org/10.1145/3350546.3352534

[83] Gordon Pennycook, Adam Bear, Evan T Collins, and David G Rand. 2020. The implied truth effect: Attaching warnings to a subset of fake news headlines increases perceived accuracy of headlines without warnings. *Management science* 66, 11 (2020), 4944–4957. https://doi.org/10.1287/mnsc.2019.3478

[84] Gordon Pennycook, Jabin Binnendyk, Christie Newton, and David G Rand. 2021. A practical guide to doing behavioral research on fake news and misinformation. *Collabra: Psychology* 7, 1 (2021), 25293. https://doi.org/10.1525/collabra.25293

[85] Gordon Pennycook, Ziv Epstein, Mohsen Mosleh, Antonio A Arechar, Dean Eckles, and David G Rand. 2019. Understanding and reducing the spread of misinformation online. *Unpublished manuscript: https://psyarxiv. com/3n9u8* (2019), 1–84.

[86] Gordon Pennycook, Ziv Epstein, Mohsen Mosleh, Antonio A Arechar, Dean Eckles, and David G Rand. 2021. Shifting attention to accuracy can reduce misinformation online. *Nature* 592, 7855 (2021), 590–595. https://doi.org/10.1038/s41586-021-03344-2

[87] Gordon Pennycook, Jonathon McPhetres, Yunhao Zhang, Jackson G Lu, and David G Rand. 2020. Fighting COVID-19 misinformation on social media: Experimental evidence for a scalable accuracy-nudge intervention. *Psychological science* 31, 7 (2020), 770–780. https://doi.org/10.1177/0956797620939

[88] Gordon Pennycook and David G Rand. 2019. Fighting misinformation on social media using crowdsourced judgments of news source quality. *Proceedings of the National Academy of Sciences* 116, 7 (2019), 2521–2526. https://doi.org/10.1073/pnas.1806781116

[89] Gordon Pennycook and David G Rand. 2021. Examining false beliefs about voter fraud in the wake of the 2020 Presidential Election. *The Harvard Kennedy School Misinformation Review* (2021). https://doi.org/10.37016/mr-2020-51

[90] Gordon Pennycook and David G Rand. 2021. The psychology of fake news. *Trends in cognitive sciences* 25, 5 (2021), 388–402. https://doi.org/10.1016/j.tics.2021.02.007

[91] Gordon Pennycook and David G Rand. 2022. Accuracy prompts are a replicable and generalizable approach for reducing the spread of misinformation. *Nature communications* 13, 1 (2022), 2333. https://doi.org/10.1038/s41467-022-30073-5

[92] Verónica Pérez-Rosas, Bennett Kleinberg, Alexandra Lefevre, and Rada Mihalcea. 2018. Automatic Detection of Fake News. In *Proceedings of the 27th International Conference on Computational Linguistics*, Emily M. Bender, Leon Derczynski, and Pierre Isabelle (Eds.). Association for Computational Linguistics, Santa Fe, New Mexico, USA, 3391–3401. https://aclanthology.org/C18-1287

[93] Markus Prior. 2009. The immensely inflated news audience: Assessing bias in self-reported news exposure. *Public Opinion Quarterly* 73, 1 (2009), 130–143. https://doi.org/10.1093/poq/nfp002

[94] Kenneth Rapoza. 2017. Can 'fake news' impact the stock market? *Forbes News* (2017). https://www.forbes.com/sites/kenrapoza/2017/02/26/can-fake-news-impact-the-stock-market/

[95] Jon Roozenbeek and Sander Van Der Linden. 2019. The fake news game: actively inoculating against the risk of misinformation. *Journal of risk research* 22, 5 (2019), 570–580. https://doi.org/10.1080/13669877.2018.1443491

[96] Larry D Rosen, Kelly Whaling, L Mark Carrier, Nancy A Cheever, and Jeffrey Rokkum. 2013. The media and technology usage and attitudes scale: An empirical investigation. *Computers in human behavior* 29, 6 (2013), 2501–2511. https://doi.org/10.1016/j.chb.2013.06.006

[97] Yoonmo Sang, Jee Young Lee, Sora Park, Caroline Fisher, and Glen Fuller. 2020. Signalling and expressive interaction: Online news users' different modes of interaction on digital platforms. *Digital journalism* 8, 4 (2020), 467–485. https://doi.org/10.1080/21670811.2020.1743194

[98] Michael Scharkow. 2016. The accuracy of self-reported internet use—a validation study using client log data. *Communication Methods and Measures* 10, 1 (2016), 13–27. https://doi.org/10.1080/19312458.2015.1118446

[99] Dietram A Scheufele and Nicole M Krause. 2019. Science audiences, misinformation, and fake news. *Proceedings of the National Academy of Sciences* 116, 16 (2019), 7662–7669. https://doi.org/10.1073/pnas.1805871115

[100] Ambika Shahu, Alexander Melem, Philipp Wintersberger, and Florian Michahelles. 2022. Nudgit - Reducing Online News Consumption by Digital Nudges. In *Adjunct Publication of the 24th International Conference on Human-Computer Interaction with Mobile Devices and Services* (Vancouver, BC, Canada) *(MobileHCI '22)*. Association for Computing Machinery, New York, NY, USA, Article 25, 5 pages. https://doi.org/10.1145/3528575.3551447

[101] Jakub Simko, Martina Hanakova, Patrik Racsko, Matus Tomlein, Robert Moro, and Maria Bielikova. 2019. Fake News Reading on Social Media: An Eye-tracking Study. In *Proceedings of the 30th ACM Conference on Hypertext and Social Media* (Hof, Germany) *(HT '19)*. Association for Computing Machinery, New York, NY, USA, 221–230. https://doi.org/10.1145/3342220.3343642

[102] Nathaniel Sirlin, Ziv Epstein, Antonio A Arechar, and David G Rand. 2021. Digital literacy is associated with more discerning accuracy judgments but not sharing intentions. (2021). https://doi.org/10.37016/mr-2020-83

[103] Megan Skillman, Caitlin Cross-Barnet, Rachel Friedman Singer, Christina Rotondo, Sarah Ruiz, and Adil Moiduddin. 2019. A framework for rigorous qualitative research as a component of mixed method rapid-cycle evaluation. *Qualitative Health Research* 29, 2 (2019), 279–289. https://doi.org/10.1177/1049732318795675

[104] Marianna Spring. 2020. Coronavirus: The human cost of virus misinformation. *BBC News* 27 (2020).

[105] Joëlle Swart. 2021. Experiencing algorithms: How young people understand, feel about, and engage with algorithmic news selection on social media. *Social media+ society* 7, 2 (2021), 20563051211008828. https://doi.org/10.1177/20563051211008828

[106] Briony Swire, Ullrich KH Ecker, and Stephan Lewandowsky. 2017. The role of familiarity in correcting inaccurate information. *Journal of experimental psychology: learning, memory, and cognition* 43, 12 (2017), 1948. https://doi.org/10.1037/xlm0000422

[107] Saravanan Thirumuruganathan, Michael Simpson, and Laks V.S. Lakshmanan. 2021. To Intervene or Not To Intervene: Cost based Intervention for Combating Fake News. In *Proceedings of the 2021 International Conference on Management of Data* (Virtual Event, China) *(SIGMOD '21)*. Association for Computing Machinery, New York, NY, USA, 2300–2309. https://doi.org/10.1145/3448016.3452778

[108] Xin Tong, Matthew Louis Mauriello, Marco Antonio Mora-Mendoza, Nina Prabhu, Jane Paik Kim, and Pablo E Paredes Castro. 2023. Just Do Something: Comparing Self-proposed and Machine-recommended Stress Interventions among Online Workers with Home Sweet Office. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) *(CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 495, 20 pages. https://doi.org/10.1145/3544548.3581319

[109] Yu-Chia Tseng, Nanyi Bi, Yung-Ju Chang, and Chien Wen (Tina) Yuan. 2022. Investigating Correction Effects of Different Modalities for Misinformation about COVID-19. In *Companion Publication of the 2022 Conference on Computer Supported Cooperative Work and Social Computing* (Virtual Event, Taiwan) *(CSCW'22 Companion)*. Association for Computing Machinery, New York, NY, USA, 54–58. https://doi.org/10.1145/3500868.3559455

[110] Melissa Tully, Emily K Vraga, and Anne-Bennett Smithson. 2020. News media literacy, perceptions of bias, and interpretation of news. *Journalism* 21, 2 (2020), 209–226. https://doi.org/10.1177/1464884918805262

[111] Jason VanTol, Maxim Nikitin, Noah Helzerman, Mark Allison, and Matthew Spradling. 2022. OpenLabel: An Open-Source Media Labeling Web Browser Extension.

[112] Chris J Vargo, Lei Guo, and Michelle A Amazeen. 2018. The agenda-setting power of fake news: A big data analysis of the online media landscape from 2014 to 2016. *New media & society* 20, 5 (2018), 2028–2049. https://doi.org/10.1177/146144481771208

[113] Christian von der Weth, Jithin Vachery, and Mohan Kankanhalli. 2020. Nudging Users to Slow Down the Spread of Fake News in Social Media. In *2020 IEEE International Conference on Multimedia Expo Workshops (ICMEW)*. 1–6. https://doi.org/10.1109/ICMEW46912.2020.9106003

[114] Soroush Vosoughi, Deb Roy, and Sinan Aral. 2018. The spread of true and false news online. *science* 359, 6380 (2018), 1146–1151. https://doi.org/10.1126/science.aap9559

[115] Emily Vraga, Melissa Tully, John E Kotcher, Anne-Bennett Smithson, and Melissa Broeckelman-Post. 2015. A Multi-Dimensional Approach to Measuring News Media Literacy. *Journal of media literacy education* 7, 3 (2015). https://doi.org/10.23860/jmle-7-3-4

[116] Sam Wineburg and Sarah McGrew. 2019. Lateral reading and the nature of expertise: Reading less and learning more when evaluating digital information. *Teachers College Record* 121, 11 (2019), 1–40. https://doi.org/10.1177/016146811912101102

[117] Xizhu Xiao and Yan Su. 2022. Wired to seek, comment and share? Examining the relationship between personality, news consumption and misinformation engagement. *Online Information Review* 46, 6 (2022), 1152–1166. https://doi.org/10.1108/OIR-10-2021-0520

[118] Xizhu Xiao and Yan Su. 2023. Stumble on information or misinformation? Examining the interplay of incidental news exposure, narcissism, and new media literacy in misinformation engagement. *Internet Research* 33, 3 (2023), 1228–1248. https://doi.org/10.1108/INTR-10-2021-0791

[119] Md Sayeed Al Zaman. 2023. Misinformation on Social Media: An Exploratory Sequential Mixed Methods Analysis of Users' Engagement with Religious Misinformation. (2023). https://doi.org/10.1177/275235432412577

[120] Amy X. Zhang, Aditya Ranganathan, Sarah Emlen Metz, Scott Appling, Connie Moon Sehat, Norman Gilmore, Nick B. Adams, Emmanuel Vincent, Jennifer Lee, Martin Robbins, Ed Bice, Sandro Hawke, David Karger, and An Xiao Mina. 2018. A Structured Response to Misinformation: Defining and Annotating Credibility Indicators in News Articles. In *Companion Proceedings of the The Web Conference 2018* (Lyon, France) *(WWW '18)*. International World Wide Web Conferences Steering Committee, Republic and Canton of Geneva, CHE, 603–612. https://doi.org/10.1145/3184558.3188731

[121] Hongxuan Zhao, Jing Xu, Timothy Onosahwo Iyendo, Oberiri Destiny Apuke, Elif Asude Tunca, and Verlumun Celestine Gever. 2023. The effectiveness of using audio-visual based media intervention for promoting social media literacy skills to curtail fake news on social media: A quasi-experimental investigation. *Information Development* (2023), 02666669231217236. https://doi.org/10.1177/02666669231217236

[122] Qi Zhou, Bin Li, Christian Scheibenzuber, and Huajun Li. 2023. Fake news land? Exploring the impact of social media affordances on user behavioral responses: A mixed-methods research. *Computers in Human Behavior* 148 (2023), 107889. https://doi.org/10.1016/j.chb.2023.107889

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